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An Expert-based Bayesian Investigation of Greenhouse Gas Emission Reduction Options for German Passenger Vehicles until 2030

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Abstract

The present thesis introduces an iterative expert-based Bayesian approach for assessing greenhouse gas (GHG) emissions from the 2030 German new vehicle fleet and quantifying the impacts of their main drivers. A first set of expert interviews has been carried out in order to identify technologies which may help to lower car GHG emissions and to quantify their emission reduction potentials. Moreover, experts were asked for their probability assessments that the different technologies will be widely adopted, as well as for important prerequisites that could foster or hamper their adoption. Drawing on the results of these expert interviews, a Bayesian Belief Network has been built which explicitly models three vehicle types: Internal Combustion Engine Vehicles (which include mild and full Hybrid Electric Vehicles), Plug-In Hybrid Electric Vehicles, and Battery Electric Vehicles. The conditional dependencies of twelve central variables within the BBN – battery energy, fuel and electricity consumption, relative costs, and sales shares of the vehicle types – have been quantified by experts from German car manufacturers in a second series of interviews. For each of the seven second-round interviews, an expert's individually specified BBN results. The BBN have been run for different hypothetical 2030 scenarios which differ, e.g., in regard to battery development, regulation, and fuel and electricity GHG intensities.

The present thesis delivers results both in regard to the subject of the investigation and in regard to its method. On the subject level, it has been found that the different experts expect 2030 German new car fleet emission to be at 50 to 65% of 2008 new fleet emissions under the baseline scenario. They can be further reduced to 40 to 50% of the emissions of the 2008 fleet though a combination of a higher share of renewables in the electricity mix, a larger share of biofuels in the fuel mix, and a stricter regulation of car CO_2 emissions in the European Union. Technically, 2030 German new car fleet GHG emissions can be reduced to a minimum of 18 to 44% of 2008 emissions, a development which can not be triggered by any combination of measures modeled in the BBN alone but needs further commitment.

Out of a wealth of existing BBN, few have been specified by individual experts through elicitation, and to my knowledge, none of them has been employed for analyzing perspectives for the future. On the level of methods, this work shows that expert-based BBN are a valuable tool for making experts' expectations for the future explicit and amenable to the analysis of different hypothetical scenarios. BBN can also be employed for quantifying the impacts of main drivers. They have been demonstrated to be a valuable tool for iterative stakeholder-based science approaches.

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List of Abbreviations

ACEA	European Automobile Manufacturers Association
BBN	Bayesian Belief Network
BEV	Battery Electric Vehicle
BMU	Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit (German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety
BMWi	Bundesministerium für Wirtschaft und Technologie (German Federal Ministry of Economics and Technology
BtL	Biomass-to-Liquid
BRS	Bayesian Risk Solutions
CNG	Compressed Natural Gas
CO_2	Carbon Dioxide
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
DI	Direct Injection
EU	European Union
EU ETS	EU Emissions Trading System
Eurobat	Association of European Storage Battery Manufacturers
GHG	Greenhouse Gas
GtL	Gas-to-Liquid
H_2	Hydrogen
HCCI	Homogeneous Charge Compression Ignition
HEV	Hybrid Electric Vehicle
HFCV	Hydrogen Fuel Cell Vehicles
ICE	Internal Combustion Engine Vehicle

ID	Influence Diagram
IPCC	Intergovernmental Panel on Climate Change
KBA	Kraftfahrtbundesamt (German Federal Motor Transport Authority)
LDV	Light Duty Vehicle
Li-Ion	Lithium-Ion (Battery)
LPG	Liquefied Petroleum Gas
NEDC	New European Driving Cycle
NGO	Non-Governmental Organisation
OEM	Original Equipment Manufacturer
PHEV	Plug-In Hybrid Electric Vehicle
PIK	Potsdam Institute for Climate Impact Research
R&D	Research and Development
REEV	Range Extended Electric Vehicles
SUV	Sports Utility Vehicle
TC	Turbo Charging
TTW	Tank-to-Wheel (Emissions)
USABC	US Advanced Battery Consortium
VDA	Verband der Automobilindustrie (German Association of the Automotive Industry)
WTT	Well-to-Tank (Emissions)
WTW	Well-to-Wheel (Emissions)

List of BBN Scenarios

BASE	Baseline Scenario
REN	Renewable Energy Scenario
BAT	Favorable Battery Development Scenario
Cpol	Strict EU Car CO_2 Emission Policy Scenario
EVInc1	Purchase Incentive for PHEV and BEV (Purchase Price Subsidy)
EVInc2	Incentive for PHEV and BEV (Fixed Electricity Price)
FP	Higher Fuel Price Scenario
BF	Greater Share of Biofuels
RBC	Combined Scenario: REN, BF, and Cpol
LowC	Low Car CO_2 Emission Scenario (Fleet Emissions Instantiated)

Chapter 1

Motivation and Aims of the Present Thesis

The design of this Ph.D. thesis is based on two main choices – on the subject level, the choice of examining greenhouse gas (GHG)[1] emission reduction options for the German automotive sector, and on the methods level, the choice of a Bayesian approach. Both choices came about rather naturally in the larger context of research carried out within the research domain 'Transdisciplinary Concepts and Methods' (TCM) at the Potsdam Institute for Climate Impact Research (PIK). In this first chapter, I give the context of and explain the motivation for both choices, and finish with a rough outline of the thesis.

1.1 The Subject of Car CO_2 Emission Development

I first started working on options for reducing GHG emissions from cars within a PIK research project on investment opportunities for a climate-friendly Germany (for the final report, see Jochem et al. (2008)), which studied the effect of the measures included in the Integrated Energy and Climate Program of the German government (see BMU (2007)) as well as additional measures. Avoiding dangerous anthropogenic climate change by reducing GHG emissions is an important topic on the German and European political agenda. German and European GHG emission reduction endeavors have been going on for a while, and different sectors have realized important emission reductions in the past years. For example, the CO_2 emissions from the German energy sector, industry, and trade, commerce and services all declined after 1990, and were reduced by 15%, 42%, and 44% until 2008, respectively. The average GHG

[1] As GHG emissions from passenger vehicle use are almost exclusively CO_2 emissions, both terms are used synonymously throughout this thesis.

emission reduction over all sectors in Germany from 1990 to 2008 was 22% (Umweltbundesamt 2010).

In contrast to other sectors, car emissions have peaked relatively lately, and emission reduction progress is lagging behind. From 1990 to 1999, German road traffic CO_2 emissions continued to rise by 14% or 22.5 million tons, largely due to backlog demand for mobility after the German reunification, but also because of a sustained trend towards larger cars and more comfort (VDA 2007a). After peaking in 1999, German road traffic emissions have been declining annually, but have dropped below 1990 levels only in 2006 (VDA 2009, p.6). According to Umweltbundesamt (2010), German traffic CO_2 emissions as of 2008 were 10% lower than in 1990.

In 1998, the European Automobile Manufacturers Association (ACEA) and the European Commission signed a voluntary agreement to reduce CO_2 emissions from new cars to 140g/km on average by 2008. Ten years later, European new fleet emissions were 153.5 gCO_2/km (T&E 2009, p.12), and the 2008 German new fleet emitted an average 165 gCO_2/km (KBA 2010), tank-to-wheel.

The moderate success in reducing new passenger vehicle emissions is all the more worrying as traffic makes up for a non-negligible share of overall emissions. In 2007, traffic caused 19% of German CO_2 emissions, and passenger cars alone contributed a share of 12% (DAT 2007, p.2). Furthermore, new cars have an average useful life expectancy of 12 years (KBA 2009a, p.4-5), such that overall fleet emissions change relatively slowly. Moreover, Germany possesses one of the leading automotive industries worldwide, such that trends in German car emissions can be assumed to have some impact on global car GHG emissions.

There is a variety of reasons why emission reduction in the traffic sector has been lagging behind. One reason may be that for many car technology related measures, it is relatively costly to save a gram of CO_2 compared to other sectors. Or that the perceived selling point of (German) cars, their driving dynamics, is inherently linked to fuel consumption and thus GHG emissions. In Germany, where the car industry is one of the most important economic sectors, the impacts of pushing for car emission reduction may be substantial. The situation is all the more threatening for German original equipment manufacturers (OEM) as on average, they produce larger and more powerful cars than other European OEM, which cause relatively high GHG emissions. Lately, the newly proclaimed policy goal of Germany becoming the world market leader for electric vehicles has added a new quality to the car emission reduction debate.

What ever the stakes, if GHG emissions are to be reduced strongly in Europe and Germany, the passenger vehicle sector is a candidate for substantial reductions. In 2007, the European Union agreed to reduce its 2020 GHG emissions by 20% below 1990 levels independently, and by 30% under a possible new global climate agreement if other major emitting countries agree to engage as well (European Commission 2010). The German government committed to reducing German GHG emissions by 40% for the same period (BMWi & BMU 2010b, p.4). In late 2008, a European regulation has been issued the aim of which is to reduce the average CO_2 emissions of all newly registered cars in the EU to 130 g/km by 2012 (for the details of the regulation, see Section 4.2.5). There is no consensus on how to reach the envisaged aim, let alone further ones planned for subsequent EU regulation steps.

Given the many open questions, and given the importance of mobility related GHG emissions on a European and global scale, an investigation of possible measures, costs, and scale of new car GHG emission reductions seems intriguing enough and has been chosen as a central aim of the present thesis.

1.2 The Method of Bayesian Stakeholder-based Science

Apart from the subject of the present investigation, the application of Bayesian methods within a strongly expert-based approach is the second characteristic of this work. This choice was suggested both by the inherent uncertainty linked to the research question, as well as by the research context.

The provision of insight into the development of GHG emissions from new cars 20 years ahead and its drivers is faced with uncertainty regarding technological development, economic development, and social choices. In such a situation, one option is to sit back and wait for things to develop, as humans cannot tell the future. However, most actors in the field cannot afford this strategy. Car manufacturers have to decide what vehicle technologies to develop, authorities have to decide which, if any, regulations to issue or incentives to offer, and consumers have to decide about their mobility needs. In such a situation, Bayesians suggest that decisions are best made on the basis of personal assessments, called priors, which incorporate all available information and can be revised as new evidence occurs.

The present approach is Bayesian in spirit as it builds on the fundamental role of subjective probabilities for decision-making under uncertainty. In Chapters 3 and 4, experts' assessments regarding the development of car GHG emissions are revealed. This shows that most of the experts interviewed hold subjective priors and are ready to quantify them in terms of probabilities. Once they have been made explicit, these expert assessments can be used as an input for other actors to base their judgement on.

The present approach is also Bayesian in a more technical sense, namely in that it applies methods building on Bayes' Rule for updating priors in the light of new information. Chapter 4 introduces a Bayesian Belief Network which has been fed with experts' priors, and which can be employed for updating these priors to hypothetical scenarios of future technology, price, or regulation development.

The present investigation is embedded within the research activities at PIK's Transdisciplinary Concepts & Methods (TCM) research domain, where stakeholder-based science is one of the strands of research pursued. This corresponds very well with the present iterative approach of revealing and processing experts' assessments as a basis for judgement in the face of uncertainty. Bayesian methods have been one focus of the research domain for several years now, and the present investigation started roughly at the time when the group 'Bayesian Risk Solutions' (BRS) was established. This offered the context for an intense discussion of Bayesian methods with the aim to develop them further, theoretically, and to extend their scope of practical applications. Within the group, we developed, e.g., a classification of Bayesian approaches presented in Chapter 2, and a methodology for diligent Bayesian Risk Management (see Fucik (2010)). The Ph.D. thesis at hand provides a strongly expert-based Bayesian Belief Network (BBN), which has been built in an iterative approach. It makes a novel contribution by extending the application of BBN to the study of future development and its main drivers, which has not been done before. It also makes the subjective assessments of different experts amenable to scenario analysis.

1.3 Outline of the Thesis

The thesis is organized as follows: In the following Chapter 2, the concepts and methods this work relies on are introduced based on a literature review. The chapter includes a general discussion of subjective probability and its role in decision-making as well as a presentation of the methods for formal Bayesian Learning and Bayesian Belief Networks. Finally, techniques for expert interviews and elicitation as well as their evaluation are discussed. The chapter focusses on what is needed as a fundament for the present investigation.

To set the scene for the analysis of car GHG emission reduction options until roughly 2020, from July through November 2007, I have interviewed 15 German automotive experts, including representatives from car manufacturers, investors, non-governmental organizations, professional associations, and science. Chapter 3 first presents the different measures suggested by these experts and the related emission reduction potentials. Subsequent sections sketch experts' assessments of the prerequisites for the different measures to be taken, and of the probabilities for their adoption. The chapter also contains an outlook which includes experts' assessments beyond the given time-frame.

Building on the outcomes of the first interview series as well as on literature review and discussion with scientists, a Bayesian Belief Network for analyzing 2030 German new car fleet emissions has been built. Parameter values have been set in accord with literature. Conditional probabilities for twelve variables have been elicited from seven experts, mostly high-ranked R&D specialists of German OEM, in February and March 2009. For each expert, an individual BBN results. The largest part of this thesis, Chapter 4, presents the BBN and the results derived from them by means of a hypothetical scenario analysis. The Sections up to 4.4 provide descriptions of the model structure and its inputs, i.e., parameters considered, equations for calculative nodes, and an exhaustive documentation of elicited conditional probabilities. Outcomes from the scenario analysis are presented in detail in Section 4.5. The final section of the chapter summarizes the results, answers the research questions which have led the investigation, and evaluates the outcomes both in regard to the research subject and the method.

Finally, Chapter 5 gives a short summary of this thesis and its main findings.

Chapter 2

Bayesian Concepts and Methods

This chapter introduces concepts and methods which are central for the Ph.D. thesis at hand. The first section deals with decision-making under uncertainty. In subsequent sections, basic elements of Bayesian reasoning are introduced, the approach of Bayesian Learning is sketched by providing an example, and the method of Bayesian Belief Networks is described. Finally, techniques for expert interviews and expert elicitation are discussed, as the case study developed in this thesis strongly relies on expert judgement.

These methods and concepts are assembled under the headline 'Bayesian' because they can all be seen as ingredients to a toolbox which allows collecting and processing subjective assessments and making them available to support decision-making under uncertainty.

2.1 Risk, Uncertainty, and Decision-Making

Situations where decisions are made vary in regard to the information available for an agent to base the decision on. When there is certainty, each alternative choice leads to a certain, known consequence. Such situations, however, are rare in regard to complex real world problems. Many decisions have to be made under circumstances of uncertainty and risk. A definition often used in decision theory differs between risk and uncertainty on the basis of how much is known on the consequences of alternative choices. Under risk, the probability of the occurrence of each possible consequence is known and can be given in the form of probability distributions over the possible outcomes for each alternative choice. In the case of uncertainty, the probability distributions on outcomes are unknown. The distinction between risk as randomness with knowable probabilities and uncertainty as randomness with unknowable probabilities goes back to Frank H. Knight (compare Fonseca & Ussher 2004) who gave this definition in his Dissertation on 'Risk, Uncertainty and Profit', first published in 1921 (Knight 2006).

Jaeger et al. (2001, p.17) propose a more encompassing definition of risk as a "situation or event in which something of human value (including humans themselves) has been put at stake and where the outcome is uncertain." According to this definition, risk implies uncertainty, but not all uncertainty is associated with risk, since risk requires that human stakes have to be involved. Conceptualizations of risk are then made up of the following elements: "type of outcome (typically, but not always, undesirable consequences); some gauging of the possibilities of occurrence (typically, but not always, probability); and type of entity affected (individual, corporate, or institutional) that also judge outcomes, their possibility, and their desirability."(Jaeger et al. 2001, pp.18f)

As an example that will be treated in this thesis, current knowledge on many factors influencing the CO_2 emissions from German new car fleets in the decades to come is imperfect. Available technology, regulation, and demand patterns can change over time, to name just a few determinants, and their development can not be reliably predicted. Moreover, it is evident that interests of many human beings are at stake, including those of OEM employees and shareholders, consumers, and people who may be affected by rising CO_2 concentrations in the atmosphere on a global scale. Thus, German car CO_2 emissions can be said to be associated with risk as defined by Jaeger et al. (2001), or with uncertainty in the classical Knightian definition.

In their book on the elicitation of probabilities, O'Hagan et al. (2006, p.217) point out that there are two different kinds of uncertainty, namely aleatory and epistemic uncertainty. They give the following definitions: "Aleatory uncertainties can be characterized as due to randomness. They are inherent, irreducible and unpredictable in nature."(O'Hagan et al. 2006, p.227) "Epistemic uncertainty is subjective in nature and arises primarily from limited or imperfect knowledge. It is, in principle, reducible by obtaining more or better information."(O'Hagan et al. 2006, p.239) The authors claim that for future events, both types of uncertainty are present (O'Hagan et al. 2006, p.224). However, in regard to the example of future German new car fleet CO_2 emissions, I find it difficult to detect the two kinds. For example, the average fuel consumption of a 2030 combustion engine vehicle, or 2030 sales shares of different vehicle types, depend on many factors the development of which is unknowable today (e.g., regulation, consumer preferences, fuel price development). But I would not agree to call them 'random', as they will result from political, social and economic choices and processes which may contain some random elements, but are not random processes in the statistical sense. Thus, although unknowable, in my view it would be more appropriate to call them epistemic, because it is possible to gather more knowledge which can contribute to a better understanding and assessment of the development.

When there is uncertainty, the outcome of actions is difficult to predict. Nevertheless, individuals are forced to make decisions. Despite uncertainty about the return on R&D expenses or consumer demand, car OEM have to decide what technologies to develop and what cars to build. Decision-making in situations with incomplete knowledge is an everyday task for individuals, and usually they do not fail to make such decisions. In the absence of certainty, they base their decisions on expectations, i.e., on what they believe will happen. Expectations draw on the knowledge and experience an agent has. They consist of a range of alternative development scenarios she considers as possible along with the probabilities she assigns to the occurrence of each of them.[1] In this sense, probabilities and expectations are based on personal beliefs and thus are subjective concepts. However, the notion of probability is controversial. A description of different interpretations is postponed to Section 2.2.1.

Decision processes can be formalized as problems of utility maximization. Then, decisions under risk can be formulated as problems of expected utility maximization. An actor's preferences over the different consequences of a decision are given in the form of a utility function. For each alternative choice, expected utility can be calculated as the sum or integral over the utility of all outcomes weighted with the probability of their respective occurrence. Rational actors should prefer the alternative which maximizes utility. Unless there is an objectively given probability distribution on outcomes, subjective probabilities play an important role in regard to decisions under uncertainty. They provide the assessment of probabilities of outcomes that is needed for maximizing (subjective) expected utility.[2] As Jaeger et al. (2001, p.76) point out, "decision analysis does not claim to yield objective results independent of the decision-maker's views or preferences. At the heart of the model lie the subjective expected utilities of an individual decision-maker."

[1] The term "expectation" as used in everyday language refers to hopes or fears of individuals. In this work, it is used in a formal sense: Mathematical expectation is calculated as the sum or integral over the products of the probability of all possible events and the values associated with their respective occurrence (Laplace 1995, p.11). This concept is used, e.g., in statistics to compute expected values or in decision theory to calculate expected utility.

[2] If the Knightian definitions of risk and uncertainty are used, subjective probabilities can be said to reduce decisions under uncertainty to decisions under risk, because they provide (subjective) probability distributions on outcomes for each alternative choice.

The above digression to decision theory has been made to illustrate the role subjective probabilities play in everyday life as well as in theoretical concepts. The thesis at hand does not treat a decision theoretical problem, but focusses on collecting experts' assessments and expectations, and on embedding them in a Bayesian Belief Network model. At its core, it is a study on the provision of expertise under uncertainty, which can then be employed in decision processes.

2.2 Bayesian Reasoning and its main Elements

Bayesianism can be traced back to the (posthumous) publication of a paper by the Presbyterian clergyman and amateur mathematician Thomas Bayes in 1763, in which he described learning from a random experiment, applying a rule of conditional probability which today is known as Bayes' Rule (Bayes 1763).[3] However, much of what is known as Bayesian statistics today was not contained in that paper, and it is unclear whether Thomas Bayes would have considered himself a Bayesian in today's sense.

The term 'Bayesianism' today connotes more than the application of Bayes' Rule, but extends to the much deeper and still controversial question of how to define probability. Bayes' Rule itself is undisputed, as Lee (1989, p.9) explains: "It should be clearly understood that there is nothing controversial about Bayes' Theorem as such. It is frequently used by probabilists and statisticians, whether or not they are Bayesians." Sober (2002) stresses that Bayesianism should not be confused with Bayes' Theorem. The author maintains that the decisive characteristic of Bayesianism is not a methodical, but a philosophical one: "The claim that all propositions have probabilities is a philosophical doctrine, not a theorem of mathematics. This is where Bayesianism begins and Bayes's Theorem leaves off. But there is more to Bayesianism than this. Bayesianism, in its strongest formulation, maintains not just that propositions have probabilities, but that all epistemological concepts that bear on empirical enquiry can be understood in terms of the probabilistic relationships described by Bayes's Theorem."(Sober 2002, p.21)

Gelman et al. (2004, p.3) give the following explanation: "By Bayesian data analysis, we mean practical methods for making inferences from data using probability models for quantities we observe and for quantities about which

[3]Gillies (2001, p.363) remarks that, with the early publication and the mathematical development added by Laplace, Bayesianism was much older than so-called 'classical statistics', the origins of which he dates to 1900 when Karl Pearson introduced the χ^2-test as the first widely used statistical test. Jaynes (1985, p.5) points out that Laplace applied Bayes' Rule successfully to a wide range of problems in astronomy, geodesy, meteorology, population statistics and jurisprudence from 1774 on.

we wish to learn. The essential characteristic of Bayesian methods is their explicit use of probability for quantifying uncertainty in inferences based on statistical data analysis." Thus, the Bayesian approach builds on a concept of probability based on degrees of belief. It makes use of subjective prior probabilities which can be revised through application of Bayes' Rule in the light of new information.

Dispute among Bayesians arises from the fact that Bayes' Rule specifies a mechanism for updating prior probabilities but does not provide any mechanism for generating these priors. This problem has attracted critique from the opponents of Bayesianism, and has led to a major controversy among Bayesians. Proponents of 'objective' Bayesianism have tried to build so called 'non-informative' priors which do not depend on subjective assessments, while 'subjective' Bayesianism has been working on diligent ways of establishing subjective priors. A prominent proponent of subjective priors is de Finetti, who holds that any belief function that satisfies the axioms of probability is rational (see Williamson & Cornfield 2001, p.1). Others require further empirical or logical constraints to be satisfied by rational belief functions. Therefore, Williamson & Cornfield (2001, pp.1f) differentiate between 'strict subjectivism' (as defended by de Finetti), 'empirical Bayesianism' (Ramsey), and 'logical Bayesianism' (Keynes), according to the restrictions imposed on belief functions. Since strong restrictions on belief functions end up leaving no room for different belief functions among rational actors having the same knowledge, Williamson & Cornfield (2001, p.2) categorize logical and empirical Bayesianism as objective Bayesianism. Because of the range of conceptual differences among Bayesian theorists, they state that "Bayesians rarely agree on the basics, even on the question of what Bayesianism actually is."(Williamson & Cornfield 2001, p.1)

While in the past, there has been a major philosophical debate on statistical methods and underlying concepts of probability, Bayesian statistics today concentrate on application, computation and models. As early as 1985, Jaynes (1985, p.13) wrote: "Today, it is our pragmatic results, far more than the philosophy or even the optimality theory, that is making Bayesianity a rapidly growing concern, taking over one after another of the various areas of scientific inference." Twenty years later, applications of Bayesian methods extends to many fields, "including business, computer science, economics, educational research, environmental science, epidemiology, genetics, geography, imaging, law, medicine, political science, psychometrics, public policy, sociology and sports."(Gelman et al. 2004, p.XX) O'Hagan (1998, p.21) points out that Bayesian statistics had greatly benefited from the development of computational power in the recent past. While in the early 1980s, computational limits had been a major concern, newly developed computational power which would now allow to use almost any representation of prior beliefs had led to a rapid expansion of Bayesian applications. They have also spread from statistics to other areas of applications, e.g., risk management. In his introduction to Bayesian risk management, Ötsch (2008) points out that the concept of subjective probability had met much less opponents among risk management practitioners than among statisticians.

Much of the current success can be explained by pragmatic advantages of Bayesianism which lie both with its possible applications and with the convenient interpretation of results. Gelman et al. (2004, p.259) see a pragmatic rationale for the use of Bayesian methods in the possibility "to combine information from different sources, while incorporating all reasonable sources of uncertainty in inferential summaries." Moreover, they hold in favor of the Bayesian framework that its "flexibility and generality allow it to cope with very complex problems. The central feature of Bayesian inference, the direct quantification of uncertainty, means that there is no impediment in principle to fitting models with many parameters and complicated multilayered probability specifications."(Gelman et al. 2004, p.4) The authors also stress practical advantages in interpreting the results from Bayesian applications: "A primary reason for believing Bayesian thinking important is that it facilitates a common-sense interpretation of statistical conclusions. For instance, a Bayesian (probability) interval for an unknown quantity of interest can be directly regarded as having a high probability of containing the unknown quantity, in contrast to a frequentist (confidence) interval, which may strictly be interpreted only in relation to a sequence of similar inferences that might be made in repeated practice."(Gelman et al. 2004, pp.3f)

However, pragmatic success does not theoretically justify the method, and the basic question of how to build priors is unsolved, theoretically. Still, expectations based on subjective degrees of belief play an important role in human decision-making, and estimations of probabilities of events or outcomes of actions often can not be based on long series of observations. Nevertheless, human beings are usually able to make decisions, and this procedure can appropriately be modeled on the basis of subjective probabilities.

In the following paragraphs, formal definitions of frequentist and subjective probability will be given, and Bayes' Rule will be deduced.

2.2.1 The Bayesian Notion of Probability

A central assumption for the case study presented later in this thesis is that individuals assign probabilities to possible (future) developments, and to outcomes of their actions, which helps them to make choices. The view of probability underlying this assumption is a subjective one, which is in contrast with the frequentist, also often called ‘classical’, definition of probability. Confusion results from the fact that sometimes, similar methods can be used to deal with different types of probability. For example, when assessing subjective probabilities, individuals are well advised also to draw on the information contained in empirical frequencies, where available. Similarly, as discussed in the previous section, both frequentists and subjectivists make use of Bayes’ Rule. Still, the ideal types of probability definitions can be clearly distinguished. In the following, first, frequentist probability is defined, followed by subjective probability.

2.2.1.1 Frequentist Probability

In a frequentist view, the probability of an event is interpreted as its long-run frequency, i.e., the proportion of times it occurs in a long sequence of trials (Berry 1996, p.114). The probability of an event A is defined as the limiting value of its frequency of occurrence when the number N of observations tends to infinity:

$$P(A) = \lim_{N\to\infty}(\frac{h_N(A)}{N}), \tag{2.1}$$

where $P(A)$ designates the probability of event A and $h_N(A)$ is the number of occurrences of event A in N observations. Thus, the probability that an event A occurs in a single observation is interpreted as its limiting observed frequency. In practice, since infinite sequences can not be observed, a probability is determined as the frequency in a large but finite number N of observations. This interpretation of probability can be applied when the event in question is the outcome of a sequence of repeatable experiments (Berry 1996, p.114). It corresponds to the definition of ‘chance’ given by Poisson, “signifying a property of events generated by repeatable random devices, measured by long-run frequencies.”(Howson 2001, p.138)

Since frequentist probability is determined from given evidence only and its estimation does not vary interpersonally, it is also called ‘objective’ probability. It is the underlying concept of classical statistical methods. Since these methods are, in practice, applied to finite numbers of trials, the exact frequency of the occurrence of an event in question within the whole population remains unknown. Therefore, e.g., parameter estimations are possible only within confidence intervals and hypothesis testing uses significance levels.

Frequentist probabilities can not be calculated when only little data is available or where experiments can not be repeated. There are no frequentist probabilities for singular events, like, e.g., a breakdown of the thermohaline circulation or atomic war. Another shortcoming of frequentist probabilities is that it is impossible to determine the number of trials needed to be within a fixed percentage of the true value of a probability. It is only possible to say how many trials are needed to be within that range with a probability of less than 100 per cent (Lee 1989, p.3). Therefore, hypotheses can be falsified, but never verified by classical testing procedures. According to Jaynes (2003, p.xxiii), due to the requirements of conditions of "independent repetitions of a 'random experiment' but no relevant prior information", frequentist methods are useful only for special cases of probability theory.

2.2.1.2 Subjective Probability

In the frequentist view, probability is an objective property of a system. This is in opposition to a definition of probability as a subjective assessment made by an individual, e.g., the observer of a system.

In the subjectivist definition, probability is interpreted as a measure of a personal degree of belief in the occurrence of an event (Berry 1996, p.121) or as a measure of uncertainty (Gelman et al. 2004, p.3). De Finetti, who defends a strictly subjectivist position, states that probability "means degree of belief (as actually held by someone, on the ground of his whole knowledge, experience, information) regarding the truth of a *sentence*, or *event* E (a fully specified 'single' event or sentence, whose truth or falsity is, for whatever reason, unknown to the person)" (Galavotti (2001, p.161), citing from de Finetti 1968, p.45).

As Howson (2001, p.138) points out, subjective probability is akin to what Poisson called "*probabilité*, signifying warranted degree of certainty relative to an agent's knowledge-state", in contrast to his definition of "chance", which relates to frequentist probability. Berry (1996, p.121) explains that subjective probabilities are present whenever a person has an opinion, which includes ignorance. In this definition, an individual can also attach probabilities to hypotheses which can be verified or falsified, given a reasonably clear definition, e.g., 'Berlin has less inhabitants than London' or 'the distance from earth to moon is roughly 100,000 km'.

In contrast to the concept of 'unknown probability' in classical statistics, subjectivists like de Finetti hold that "Probability as *degree of belief* is surely known by anyone."(Galavotti (2001, p.164), citing from de Finetti 1973, p.356) The opposite statement, namely that "probability does not exist", can be found in de Finetti's work as well. However, this relates to an objectively 'true' probability, which he rejected as a metaphysical or theological notion (Galavotti 2001, p.167).

Subjectivists agree that probabilities should take prior knowledge and beliefs into account and ought to conform to the axioms of probability calculus known as the Kolmogorov axioms (Williamson & Cornfield 2001, p.1). Subjective probabilities can change as new information becomes known. According to Berry (1996, p.121), the value of a subjective interpretation of probability for statistics lies in this very feature. Formally, initial subjective probabilities are revised in the light of new evidence through the application of Bayes' Rule. This rule will be introduced in the following section.

2.2.2 Bayes' Rule

Bayesian methods are built on a rule for the calculus of conditional probabilities, originally published in Bayes (1763), and today known as Bayes' Rule or Bayes' Theorem.

To keep things formally simple, suppose that we are interested in the probability that some event B occurs (or that some proposition B is true). We know the unconditional probability of B, $P(B)$[4], which may be our degree of belief in B. We then find out that another event A has occurred. We can now adapt our $P(B)$ on the basis of the new information. To this aim, we want to calculate the conditional probability of B given A, $P(B \mid A)$, which can be done by Bayes' Rule.[5]

In order to draw conclusions on B from information about A, the joint probability of A and B is required, which is the probability that both events occur simultaneously. Simultaneous occurrence of two events is represented by their intersection $(A \cap B)$ which corresponds to the logical 'and'. Joint probabilities and conditional probabilities are related as follows through the *multiplication rule* of probability theory:

[4] Strictly seen, $P(B)$ is a conditional probability, since it depends either – as a subjective probability – on the current state of knowledge and experience of an actor, or – as an 'objective' probability – on the method applied to make it 'non-informative'. Thus, it should be written as a conditional probability, e.g., $P(B \mid C)$, where C represents the current knowledge. For the deduction of Bayes' Rule, the conditioning C is omitted to keep notation simple. However, it is important to remember that all (subjective) probabilities are conditional probabilities. For a conditional version, see Jaynes (1985, p.5).

[5] The notation and the deduction of Bayes' Rule follows loosely that given by Berry (1996, pp.124-153).

$$P(A \cap B) = P(B \mid A)P(A), \tag{2.2}$$

and, symmetrically,

$$P(A \cap B) = P(A \mid B)P(B). \tag{2.3}$$

If $P(A) > 0$, **Bayes' Rule** is obtained from equations 2.2 and 2.3 as

$$P(B \mid A) = \frac{P(B)P(A \mid B)}{P(A)}. \tag{2.4}$$

In Equation 2.4, Bayes' Rule is given for the simple case of two events A and B which both have a single outcome and probability. A generalization of the rule is straightforward. If there is a finite number of mutually exclusive and exhaustive events B_i $(i = 1, ..., n)$, the denominator in 2.4 can be expanded by use of the law of total probability

$$P(A) = \sum_{i=1}^{n} P(A \mid B_i)P(B_i). \tag{2.5}$$

Bayes' Rule for calculating the conditional probability of each event B_i, given A, then becomes

$$P(B_i \mid A) = \frac{P(B_i)P(A \mid B_i)}{\sum_{i=1}^{n} P(B_i)P(A \mid B_i)}. \tag{2.6}$$

When there is a range of mutually exclusive and exhaustive possible events B_i, the probabilities over all events have to sum up to unity. Analogously, there may be not just one event A, but different possible events A_j $(j = 1, ..., n)$. Then, for each B_i, there is a probability distribution assigning probability values to each alternative A_j to occur under this condition. This distribution is called the likelihood function. It describes to which degree different pieces of evidence A_j support a given proposition B_i. Likelihood values over all A_j sum up to unity for each given B_i.

2.2.2.1 Dynamical Bayes

Bayes' Rule is often interpreted and applied in a dynamical fashion. While Bayes himself has not introduced it this way, dynamical applications are what Bayes' Rule derives much of its present-day fame from.

In the dynamical perspective, Bayes' Rule is seen to provide a mechanism for learning from data sets such as time series. It describes how "prior" probabilities, that is, probabilities held on the basis of all knowledge prior to new evidence, change in the light of such new information. In the simple version of

Bayes' Rule given in Equation 2.4, $P(B)$ is called the *prior probability* of B. The conditional probability $P(B \mid A)$ is named the *posterior probability* of B, because it is the updated probability an individual assigns to B after having learned from A. Thus, Bayes' Rule is taken to supply a mechanism for inference, indicating how to learn about B from data A: The posterior probability is proportional to the product of the prior probability $P(B)$ and the *likelihood* of evidence A, $P(A \mid B)$.

To make things more plastic, let us rewrite the version where the probabilities of a finite number of mutually exclusive and exhaustive events are considered (given in Equation 2.6) in the following way:

$$P(h_i|\, e_{t+1}) = \frac{P(h_i|\, e_t)P(e_{t+1}|\, h_i)}{\sum_{j=1}^{n} P(h_j|\, e_t)P(e_{t+1}|\, h_j)} \tag{2.7}$$

Now, h_i , $i = 1, ..., n$ can be considered a set of n hypotheses or models, e_t a time series of observations up to point t in time, and $P(h_i|\, e_t)$ the prior probability of a hypothesis h_i at time t. When new data e_{t+1} becomes known (an observation at time $t + 1$), the updated weight of each of the hypotheses h_i, i.e., $P(h_i|\, e_{t+1})$ can be calculated as described in Equation 2.7. In the next step, the resulting posterior probability can be used as a prior.

Thus, Equation 2.7 describes how to sequentially adapt the weight of a set of hypotheses in the light of new knowledge. It may seem straightforward, intuitively, to apply Bayes' Rule in this dynamic fashion, and it is used this way in many applications. However, the dynamic updating rule does not directly follow from Bayes' Rule. The missing link is provided by a well-known theorem introduced by de Finetti, which shows that a Bayesian Learning process converges when applied to a sequence of exchangeable[6] random variables.

For the case of 0-1 random variables (events that may or may not happen), Heath & Sudderth (1976) say that according to de Finetti's theorem, "every sequence of exchangeable 0-1 random variables is a probability mixture of sequences of independent, identically distributed variables" (Heath & Sudderth 1976, p.188).

As de Finetti has shown, the assumption of exchangeability in subjectivist Bayesianism assures that, for large numbers of observations, the posterior probability of an event will tend to the observed frequency, no matter how the prior probability has been assigned (Gillies 2001, pp.369-371). This finding justifies using Bayesian Learning for adapting expectations to new findings when

[6]The following definition of exchangeability is given by Galavotti (2001, p.163) for the case of events (i.e., 0-1 random variables): "events belonging to a sequence are *exchangeable* if the probability of h successes in n events is the same, for whatever permutation of the n events, and for every n and $h \leq n$".

faced with an exchangeable sequence of data, and reduces the importance of the choice of a prior, as long as a large amount of data is available.

The original source for de Finetti's theorem is de Finetti (1937); for an English translation, see de Finetti (1964). A relatively simple proof of the theorem for 0-1 random variables is given in Heath & Sudderth (1976). Kreps (1988, pp.145-164) deduces the implications of de Finetti's theorem for a Bernoulli random variable (the probability of a tossed tack landing on its side) in a way at the same time entertaining and very instructive. He then also gives a generalized version of the theorem.

The above discussion refers to the case of 0-1 random variables, or 'events' that may or may not occur. This version applies to, e.g., a Bayesian approach for learning which one out of a set of hypotheses is true. De Finetti's theorem can be generalized to encompass more complex forms of random variables, which, however, is beyond the scope of this thesis.

2.2.2.2 Continuous Bayes

Bayes' Rule can also be applied when there are infinitely many possible events. For a simpler notation, Equations 2.6 and 2.7 can be written as proposed by Gelman et al. (2004, p.8):

$$p(\theta \mid y) = \frac{p(\theta)p(y \mid \theta)}{\sum_\theta p(\theta)p(y \mid \theta)}, \tag{2.8}$$

where θ denotes a vector of propositions on unobservable quantities or parameters to draw conclusions about and y is the observed data to condition on. In case of continuous θ, the sum in the denominator of formula 2.8 is replaced by an integral:

$$p(\theta \mid y) = \frac{p(\theta)p(y \mid \theta)}{\int_0^\infty p(\theta)p(y \mid \theta)d\theta}. \tag{2.9}$$

Prior probabilities $p(\theta)$ and posterior probabilities $p(\theta \mid y)$ then take the form of continuous probability density functions. If the events to condition on, y, take continuous values as well, the likelihood function $p(y \mid \theta)$ is also a continuous probability distribution.

In the following paragraph, a categorization of Bayesian approaches will be proposed on the basis of the elements introduced in this section, so far.

2.2.3 Categorization of Bayesian Approaches

As described in the previous two paragraphs, there are two main constitutive elements for Bayesianism: Subjective probability, and the application of Bayes'

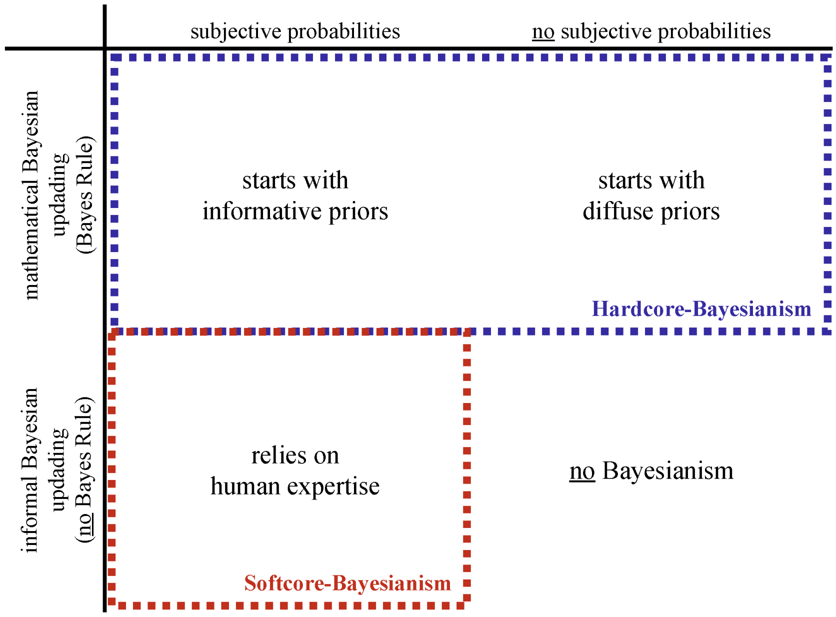


Figure 2.1: Category Scheme of Bayesian Approaches
Source: Courtesy of Fucik (2010, p.7)

Rule. Within our research group 'Bayesian Risk Solutions' (BRS) at Potsdam Institute for Climate Impact Research and University of Potsdam, we have developed a category scheme of Bayesianism which builds on whether these two elements are contained in an approach. The scheme is displayed in Figure 2.1. The four-field matrix is divided by whether subjective probabilities are used (left fields: subjective probabilities versus right fields: no subjective probabilities), and by whether Bayes' Rule is employed (upper fields: formal updating by Bayes' Rule versus lower fields: informal updating).

For formal applications of Bayes' Rule, we have coined the term 'hardcore Bayesianism', and informal updating is called 'softcore Bayesianism'. An approach where neither formal updating occurs nor subjective probabilities are employed cannot be called Bayesian (field on the lower right). The question of whether the top right field of the category scheme, where no subjective inputs are used, but formal updating is carried out, actually belongs to (hardcore) Bayesianism can be disputed – a dispute which could not be settled within our working group. As Bayes' Rule is also used in frequentist statistics, obviously, not every application of Bayes' Rule to non-subjective probabilities can be subsumed under Bayesianism.

In the following, different approaches of 'hardcore' and 'softcore' Bayesianism will be discussed.

2.2.3.1 Bayesian Reasoning based on Data

The so-called ‘hardcore’ Bayesian approach refers to the application of Bayes’ Rule within a formal framework. This can be done whenever data is available for the analysis of a problem. Using Bayes’ Rule, data can be employed to update a set of previously defined a prioris.

Several hardcore Bayesian approaches have been applied in the framework of the BRS working group. These include:

- Bayesian Learning: Defining a set of hypotheses with initial prior probabilities, and adjusting the latter by Bayes’ Rule. The details of the procedure will be described in Section 2.3. I have worked on two different applications. The first regards the development of agricultural yield expectations in Germany and uses diffuse prior probabilities, thus can be placed in the upper right panel of Figure 2.1 (see Krause 2008). The second aims at quantifying the fraction of Swiss summer heatwave risk attributable to anthropogenic climate change, and is based on a Bayesian learning approach with different sets of informative priors, i.e., is an example for the upper left category in Figure 2.1 (see Jaeger et al. 2008).

- Bayesian Belief Networks (BBN): They use a graphical model of conditional independencies combined with a probabilistic model. BBN software implements Bayes’ Rule for adapting the network to new information. The method is described in detail in Section 2.4. Chapter 4 of this thesis introduces an expert-based BBN, which is, again, an example of the upper left panel in Figure 2.1.

- Bayesian Parameter Estimation: In contrast to point estimates provided by frequentist statistics, Bayesian approaches allow fitting distributions which reflect uncertainty in the underlying data. In his Ph.D. thesis, Fucik (2010) gives a broad overview of available methods. In their paper on the Swiss summer heatwave in 2003, Siliverstovs et al. (2009) provide an example of how to use Bayesian parameter estimation for analyzing structural breaking points in data.

While data processing in hardcore Bayesianism follows a given rule, the provision of hypotheses and their initial probabilities does not, as has been discussed. Especially in the case of subjective probabilities, the choice of initial probabilities is at the discretion of the risk analyst or the author of the respective study. For example, in the second Bayesian Learning application mentioned (Jaeger et al. 2008), priors have been based on a diligent literature review. In the case of the BBN which is developed in this thesis, large parts of the network specifications have been generated through expert interviews and elicitation. This exemplifies the degree of subjectivity that may be present in subjective hardcore approaches.

2.2.3.2 Bayesian Reasoning in the Absence of Data

In so-called 'softcore' Bayesianism, subjectivity is extended to the learning aspect. This approach is not feasible without subjective probabilities, such that there exists no 'objective' branch of softcore Bayesianism in Figure 2.1.

Within the BRS research group, we have decided to extend the notion of 'Bayesian' to approaches which build on the concept of subjective probability, independently of whether a formal Bayesian learning process is carried out. This explains why in this thesis, tools such as expert interviews and elicitation are subsumed under Bayesian methods: They serve to identify the subjectively held priors (or parts thereof) of individuals.

We assume that, for making decisions under uncertainty, individuals form subjective priors, i.e., they think about the possible outcomes resulting from different decision options, and about how likely it seems to them that each of those options will be realized. Although the concept of prior probability distributions and Bayesian updating is unknown to many individuals, we assume that individuals unconsciously perform such reasoning. In this setting, Bayes' Rule is a prescription of how to rationally incorporate new information into the priors. The question of whether or not implicit updating obeys Bayes' Rule is difficult to answer. In many cases, priors are not formalized, and new knowledge is not of a form that permits applying the formal mechanism. However, there exists some evidence that humans tend to adapt their views insufficiently to new information. This phenomenon may be related to the anchoring affect discussed in Section 2.5.3.

We suppose that individuals do learn from new information, and we include these processes and their analysis into a wider Bayesian framework. This analysis is faced with some difficult problems. For example, the formal approach discussed before does not sketch the coming into being of a set of hypotheses, nor the transformation of this set when options nobody has thought of before suddenly appear. For modeling such developments, genetic algorithms could be employed (see Haas (2009)). However, such approaches are beyond the scope of what the BRS group has worked on in the past years.

For the time being, the attention to the softcore approach in this thesis is restricted to techniques for deriving hypotheses and initial subjective probabilities, which the softcore approach shares with the subjective hardcore strand of Bayesianism. When data is scarce, experts' assessments are a prime source for information on possible hypotheses and their initial weights. Techniques for expert interviews will be presented in Section 2.5.1, and have been applied for gathering background information for modeling CO_2 emission reduction options for the German car industry in Chapter 3. The art of eliciting probability distributions from experts will be dealt with in Sections 2.5.2ff. Elicitation has been applied for quantifying initial probabilities for a Bayesian Belief Network on 2030 German new car fleet CO_2 emissions and is documented in Chapter 4.

2.3 Formal Bayesian Learning

In a formal framework, Bayes' Rule can fruitfully be employed for learning from new information. While different versions of the rule have been presented in Section 2.2.2, in the present section, a description of how to employ it in a formal analysis will be given. The steps of the analysis will be exemplified along an updating approach to Swiss German agricultural yields, a more rigorous description of which can be found in Krause (2008). In this application, the weights of different hypotheses on cereal yield development are updated in accordance with data. Bayesian parameter estimation makes use of similar techniques for updating uncertainty on model parameters. See Fucik (2010) for an overview of methods and Siliverstovs et al. (2009) for an application.

A formal updating procedure consists of a number of consecutive steps. Gelman et al. (2004, p.3) subdivide the process of Bayesian data analysis into the following three tasks :

1. Setting up a probability model providing a joint probability distribution for the observable and unobservable quantities in a problem.

2. Conditioning on observed data.

3. Evaluating the fit of the model.

If the evaluation shows that the model is poor, steps 1 throughout 3 are repeated. Below, these steps are described in more detail.

2.3.1 Setting up a Probability Model

The probability model is made up of a joint distribution of hypotheses θ and data y, which indicates the probabilities of hypotheses being true and data occurring simultaneously. As is known from the multiplication rule (given in Section 2.2.2, Equation 2.2), the joint distribution $(\theta \mid y)$ is equivalent to the product of the likelihood function $p(y \mid \theta)$ and the prior probability distribution $p(\theta)$. Thus, a probability model that Bayes' Rule can be applied to consists of

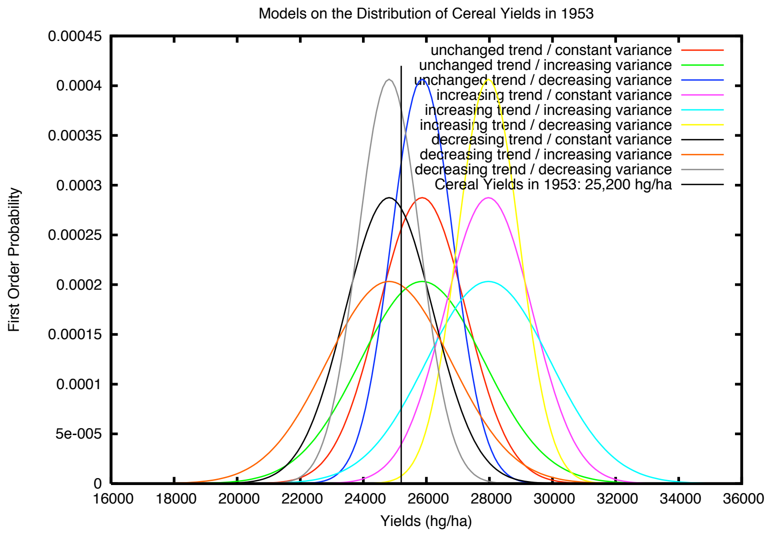


Figure 2.2: Set of Hypotheses on German Cereal Yields in 1953

- a set of hypotheses or models, giving the likelihood of data within them, and
- a prior probability distribution over hypotheses.

These two elements will be described in the following two paragraphs.

2.3.1.1 Defining Hypotheses

An agent can consider several hypotheses or models on unknown quantities or parameters she wants to learn about. These hypotheses usually take the form of probability distributions on observations.

For example, in Krause (2008), the hypotheses are a set of probability distributions for agricultural yields in the coming period. For each updating period, i.e., each year from 1953 to 2006, there are nine different hypotheses on yield distributions. They are derived from past yield data up to that year, guided by the assumptions that the (linear) yield trend may persist, or its slope may increase or decrease by 20%, and that (normally distributed) variance may persist, increase or decrease by 20%. For a formal definition of the hypotheses, see Krause (2008, p.13). As an example, the nine hypothetical distributions of cereal yields considered for the year 1953 are shown in Figure 2.2.

For each of the j distributions θ_j, a likelihood function $p(y \mid \theta_j)$ exists which specifies the probability of yields y to occur within the hypothesis under consideration. As the likelihood function is continuous, likelihood can not be calculated for a discrete value of y, but only for (possibly very small) yield intervals. Likelihood is also called ‘first order probability’.

The hypotheses chosen should reflect the agent’s personal state of knowledge. Ideally, the set of hypotheses should contain all possible alternatives. However, as Jaynes (1985, p.3) points out, “we cannot be sure that our hypothesis space H_0 is the same as Nature’s hypothesis space H_N”. Critics of Bayesian methods hold that they are invalid unless H_N is known. Jaynes (1985, p.3), on the contrary, argues that “our goal is not omniscience, but only to reason as best we can with whatever incomplete information we have”. This can be done by departing from a set of hypotheses determined on the basis of current knowledge and adjusting it whenever it proves wrong.

2.3.1.2 Assigning Prior Probabilities

The second element needed is an initial prior probability distribution over the set of hypotheses, $p(\theta)$. It is a ‘initial prior’ distribution because it is conceived before experience. It assigns probabilities that each hypothesis is true on the basis of the state of knowledge held before updating. The prior probability density assigns so-called prior ‘second order probabilities’, or weights, to the hypotheses (which, in turn, assign first order probabilities to possible observations as described above).

If initial probabilities are conceived as subjective degrees of belief, agents may differ in their assessments of initial probability densities. However, the individual freedom in choosing initial priors is disputed among Bayesians, as discussed in Section 2.2. Some argue that the requirement of rationality substantially narrows down subjectivity in the choice of priors. Jaynes (2003, p.373) claims that “inferences are to be completely ‘objective’ in the sense that two persons with the same prior information must assign the same prior probabilities”.

The discussion goes back to Laplace who introduced the ‘principle of insufficient reason’, which determines probabilities before experience: If the agent setting up priors has little or no information to base her choice on, uniform priors have to be chosen. Williamson & Cornfield (2001, p.2) resume the principle saying that “if there is no known reason for asserting one out of a number of alternatives, then all the alternatives must be given equal probability”. They state, however, that the principle was not coherently applicable when there was more than one set of suitable alternatives. Jaynes (2003, p.373) therefore proposes the maximum entropy principle as a more general rule. Under complete ignorance and if there is a finite set of possibilities, the maximum entropy principle favors uniform prior probability distributions. For continuous probabilities, however, the problem becomes mathematically much more complex.

Swinburne (2002, p.12) objects to the principle of indifference, arguing that "one can make no judgements of prior probability in advance of any evidence". Among subjectivist and objectivist Bayesians, it is disputed whether there are "a priori criteria of prior probability and these allow us to ascribe intrinsic probabilities to all hypotheses", which Swinburne (2002, p.17) affirms. Albert (2001, p.344), on the contrary, argues that the existence of rational priors before experience had not been proven and that a revival of this idea was unpromising.

If subjective initial prior probabilities of actors are accepted, such personal degrees of belief can, in practice, be revealed through calibration experiments. For example, to determine the subjective probability an agent assigns to the occurrence of event A, she is asked to choose either a lottery with an objective expected value (e.g., drawing a red ball from an urn with known composition) or a bet on event A, both yielding the same prizes. Chances in the lottery are adjusted (e.g., by changing the composition of the urn) until the agent is indifferent between the lottery and the bet. At this point, the agent's subjective probability that event A will occur corresponds to the probability of winning in the lottery.

The influence of the prior second order probability assessment on the posterior probability distribution derived by application of Bayes' Rule depends on the number of hypotheses considered and the amount of data available. Gelman et al. (2004, p.39) claim that the prior distributions do not necessarily have to be concentrated around the actual value, as the information used for updating will adjust the initial specification. Figuratively, it can be said that the prior washes out in the process of Bayesian learning as more and more data becomes available. Swinburne (2002, pp.15f) points out that for a small number of hypotheses and a large collection of data, the initial allocation of prior probabilities often will not be very important. Under the assumption of exchangeability, for large numbers of observations, the posterior probability will converge to the observed frequency independently of the prior probability assigned (see the discussion of de Finetti's Theorem in Section 2.2.2).

For the example application of updating German agricultural yield expectations over time, uniform priors have been used. This was done in accordance with the principle of insufficient reason, and to give each of the hypotheses an equal chance to gain weight in the light of data.

2.3.2 Conditioning on Observations

Having specified a probability model, the actual learning process takes place through application of Bayes' Rule. The prior probability distribution p(θ) is revised by conditioning on observations (y) and a posterior distribution $p(\theta \mid y)$ is generated. This means that "initial beliefs, represented by prior probabilities, are combined by Bayes' Theorem with information in data, incorporated in the likelihood function, to yield posterior probabilities relating to parameters or hypotheses."(Zellner 1975, p.40)

Thereby, a shift in the second order probabilities of hypotheses takes place, which alters their relative weight in the calculation of expectations. This process is called Bayesian conditionalization, updating the prior, updating second order probabilities, or Bayesian Learning.

In iterative updating processes, the posterior second order probability distribution serves as a new prior distribution for the consequent updating step. Thus, Bayesian learning is modeled as a dynamic process. This has been done in the updating approach on German agricultural yields which has been sketched as an example throughout this section. In this approach, the dynamic version of Bayes' Rule (the same one as presented in Equation 2.7 and critically discussed in Section 2.2.2) is used for updating:

$$P(h_i|\, e_{t+1}) = \frac{p(e_{t+1}|\, h_i) \cdot P(h_i|\, e_t)}{\sum_{j=1}^{n} p(e_{t+1}|\, h_j) \cdot P(h_j|\, e_t)},$$

where h_i , $i = 1, ..., 9$ is the set of hypotheses on yield development and e_t is yield data observed up to a point t in time, such that $P(h_i|\, e_t)$ is the prior probability of a hypothesis at time t. When new data e_{t+1} becomes known (yield data of year $t + 1$), the updated second order probabilities $P(h_i|\, e_{t+1})$ can be calculated. In the next step, this result will be used as a prior.

The updating process can be illustrated within Figure 2.2. Actual 1953 German cereal yields were 25200 hg/ha as indicated by the black line. The updating rule prescribes that the likelihood of this data within each of the hypotheses has to be calculated[7], and the weights of all hypotheses are adjusted in accordance with the relative likelihood of data within them. For example, actual 1953 German cereal yields were most likely within hypothesis no. 9 (decreasing trend and decreasing variance, grey line in Figure 2.2), such that the prior weight of this hypothesis was multiplied with the highest factor to derive its posterior probability, which then served as a prior for the next updating step.

[7]In practice, the likelihood of yields within a small interval around observed yields is calculated, as the likelihood of a discrete yield value is zero under a continuous distribution.

Similarly, the prior probabilities of all other hypotheses were adapted according to the likelihood they assigned to cereal yields of (roughly) 25200 hg/ha.

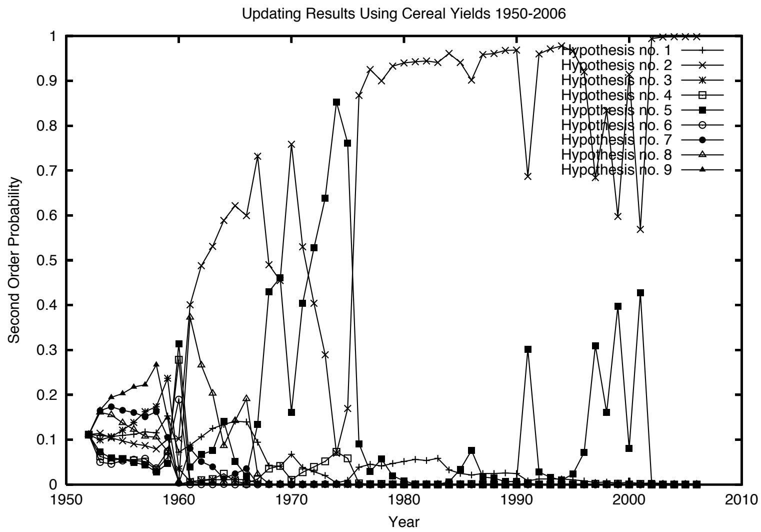


Figure 2.3: Updating Results on German Cereal Yield Development Hypotheses

The development of the weights assigned to the nine cereal yield hypotheses over time as resulting from the updating procedure are shown in Figure 2.3. It shows that in the final years of updating, hypothesis no. 2 (unchanged trend and increasing variance) gains nearly a full 100% of weight. The second most important hypothesis over much of the updating period has been hypothesis no. 5 (both trend and variance increase). For a detailed description, see Krause (2008).

2.3.3 Evaluating the Fit

As the discussion on the generation of the probability model has shown, it is by no means clear how a model can be set up in order to guarantee that it represents real-world features in a satisfactory manner. Updating the weights of different hypotheses does not assure that any of them fit reasonably well, since it only redistributes probability according to the information contained in the data. If none of the models under consideration corresponds to reality, those which are most compatible (or least incompatible) with data will gain weight in the probability distribution. As Gelman et al. (2004, p.157) put it, “Bayesian prior-to-posterior inferences assume the whole structure of a probability model and can yield misleading inferences when the model is poor". Therefore, the fit of the probability model has to be evaluated carefully. According to the authors, the evaluation has to deal with the questions, "does the model fit the data, are the substantive conclusions reasonable, and how sensitive are the results to the modeling assumptions"(Gelman et al. 2004, p.3)?

There are different methods which can be applied for checking the model. A detailed description is given by Gelman et al. (2004, pp.157-190). They propose the following methods:

- *Sensitivity Analysis*: Setting up other reasonable probability models and comparing how much results differentiate from those generated by the favored model.
- *Do the inferences make sense?* Using additional information not incorporated into the model to check if they contradict updating results.
- *Posterior predictive checking*: Comparing simulated values from the posterior predictive distribution to observed data.
- *Graphical posterior predictive checking*: Displaying observed data alongside simulated data from the model.
- *Numerical posterior predictive checks* via the comparison of test quantities calculated on observed data with values obtained from a predictive distribution for replications.

If it is found that the model does not fit reasonably well, it can be altered or expanded to include new hypotheses. Then, the updating and evaluation procedure is repeated. As Jaynes (1985, p.4) proposes, each time the predictions from calculations based on the initial hypothesis space turn out to be wrong, a better hypothesis space can be defined and calculations are repeated.

2.4 Bayesian Belief Networks

Bayesian Belief Networks (BBN) are another method which employs formal Bayesian Learning. In this section, the method will be introduced, which will be done in some detail, as a BBN application is at the core of this thesis. While a more precise technical definition will be given later (see Section 2.4.3), I am first going to give an intuition about how BBN work and what they can be used for. Bayesian Belief Networks consist of

- a graphical representation of qualitative relationships among variables,

- with a probabilistic model superimposed.

The graphical model is made of so-called nodes or vertices which represent variables, with directed edges or links between them. Edges represent some influence of one variable on another, or sometimes a stronger causal dependency. For a simple example, see Figure 2.4 placed in Section 2.4.4.2. Such a graph can be used to structure a problem in an intuitive way, without worrying about quantified relationships or the strength of influences in a first step. In a second step, a probabilistic model is set up which quantifies conditional probabilities for each variable, given the configurations of variables which were found to have an influence on it when setting up the graphical model.

BBN can be used for probabilistic reasoning under uncertainty. They allow for dependencies within a domain to be modelled, and influences of variables on others to be explained or made explicit. They can be used for decision support when decisions in complex areas involving uncertainty have to be made. One of the advantages of BBN is that new information about the state of one or several variables can be entered and propagated throughout the network by help of a learning mechanism, such that all probabilities are adapted to the new state of knowledge. Bedford & Cooke (2001, p.286) describe BBN as "convenient tools for making inferences about uncertain states when limited information is available". Available specialized software allows such computations to be made quickly and efficiently.

Another advantage is that for the construction and specification of such a network, multiple sources of knowledge can be used and labor can be effectively divided among contributors with different kinds of expertise or skills. For example, a modeller can set up the graphical network with the help of experts of the domain in question, asking them which variables to consider and how to structure their relations. Then, she can use data or expert elicitation or both in order to generate the probabilistic model. Finally, a decision-maker can use the BBN, entering own findings or assumptions to check possible results of alternative decisions.

There is a large number of areas of application. Bedford & Cooke (2001, p.286) report that BBN are used for making diagnoses in medical science as well as in various engineering disciplines, particularly emergency planning. BBN are also used in Microsoft Products, e.g., the answer wizard, the office assistant, or for technical support. The NASA "Vista" system has used BBN for interpreting live telemetry and providing advice on the likelihood of alternative failures of space shuttle propulsion. There are many more applications in genetics, speech recognition, and data compression (Murphy 1998). To date, a large chunk of applications come from the area of artificial intelligence. Applications where elicitation is used as an input for structuring or quantifying a BBN will be discussed in more detail in Section 2.5.7.

There is some confusion on the notion of BBN and what exactly it refers to. First, different authors use different names, e.g., Bayesian Networks, Belief Networks, Bayesian Belief Networks, or Causal Networks (Neapolitan 1990, p.153). Second, there is some fuzziness in the definition of BBN and the differences between BBN and a related kind of networks which are called Influence Diagrams. The following section aims at clarifying the latter issue.

2.4.1 Bayesian Belief Networks and Influence Diagrams

Bayesian Belief Networks (BBN) and Influence Diagrams (ID) both build on graphical models. For both, the graph uses nodes linked with directed edges, and shares the same structural requirement, namely that the graph has to be acyclic (for a definition, see Section 2.4.3).

However, the purposes of BBN and ID are not the same. According to Bedford & Cooke (2001, p.287), the main emphasis in a BBN is to conduct Bayesian inference, i.e., to calculate posterior probabilities of certain variables, given observations on the state of others. In contrast, the aim of an ID is to determine optimal decisions. The different goals of networks are conveyed by the nodes they use, which differ in nature. Bedford & Cooke (2001, pp.289) differentiate four kinds of nodes, namely:

- *Chance Nodes*: Nodes which give probabilities of the variable being in each of its possible states.
- *Deterministic Nodes*: Nodes that can be used to represent fixed quantities or variables depending on others in a deterministic fashion.
- *Value Nodes*: Nodes which assign values or utilities, given the states of the other variables in the problem.
- *Decision Nodes*: Nodes that represent the alternative options a decision-maker is faced with.

Bedford & Cooke (2001, pp.287) say that of the four node types, BBN would contain only one, namely chance nodes. In contrast, the presence of a decision node was characteristic for an ID, which also included a value node. Different authors go conform with this description of ID. Neapolitan (1990, p.153) says that influence diagrams are Bayesian Belief Networks (or causal networks, as he calls them throughout his book) augmented with decision nodes. Similarly, Oliver & Smith (1990, p.386) point out that “Influence diagrams are essentially identical to belief networks, but, in addition to chance variables representing uncertain states of the world, they also contain decision variables and value variables."

Howard & Matheson (2005, p.127), however, say that ID can be used for constructing both deterministic and probabilistic models. The deterministic case is in contrast to the idea of an augmented BBN, because by definition, the probabilistic model is an integral part of any BBN. Thus, they can not be purely deterministic, and consequently, this statement proposes that ID are not necessarily BBN with additional node types, but can be very different in nature.

Returning to the description of BBN given by Bedford & Cooke (2001), we can see that it is quite selective, confining them to contain chance nodes only. The definition of BBN given by Cowell et al. (1999, p.21) leaves room for a more liberal interpretation. They say that a BBN is a system of a (directed acyclic) graph representing qualitative relationships between variables with a superimposed joint probability model. This allows for nodes other then chance nodes, as long as they do not interfere with the joint probability model. It is easy to imagine, e.g., a deterministic node added to a BBN as a function of one or more chance nodes, probabilities of which would result from the probabilities of the nodes it is a function of.

From the above, it can be concluded that both for BBN and ID, there is no undisputed definition which clarifies what kind of nodes may and may not be used. In practice, differentiation between the two kinds of network is not very strict, e.g., networks containing a decision node can be found that are termed BBN by their authors. For example, in his introduction to Bayesian Belief Networks, Jensen (1996, pp.18f) says that (conditional or unconditional) probability tables are attached to any node in a BBN, which conforms to a strict definition of BBN containing only probability nodes. However, in a later section, BBN including 'action' and 'utility' nodes are presented (Jensen 1996, pp.135ff). The latter hold utility tables, not probability tables, and thus the network should not be called a BBN but an ID under a strict definition. ID are mentioned only once throughout the book (Jensen 1996, p.149): "In graphical representations of decision problems, a link from a variable V to an action variable A indicates that the state of V is known when deciding on A. Such representations are called *influence diagrams*." Although this quote suggests that the author generally conforms with calling networks including a decision node ID, he does not stick to this rule.

Summing up, it is possible to differentiate BBN and ID according to what nodes they contain. In practice, however, this differentiation is not handled very strictly. For the present purposes, it suffices to know that this thesis includes a BBN in the sense of Cowell et al. (1999), i.e., a graphical model with a joint probability distribution over its variables. This allows for deterministic nodes to be added where convenient. The BBN presented in Chapter 4 will not contain any value or decision nodes.

Now that a rough description of BBN has been given, later sections will provide a technical definition (Section 2.4.3) and a stepwise introduction into the construction of BBN (Section 2.4.4). To this purpose, some graph theoretical definitions will be needed, which are provided in the following section.

2.4.2 Some Graph Theoretical Basics

In this section, some basic graph theoretical definitions are given which are needed for understanding and describing Bayesian Belief Networks. In the literature, definitions and notation vary. The presentation given here is based on the introduction to graph theory given by Cowell et al. (1999, pp.44ff), unless indicated otherwise. For readers who do not want to read through this section, or for later reference, a summary of the definitions used is provided in Table 2.1.

Table 2.1: Basic Graph Theoretical Definitions

(Table continued on next page)

Item	Definition	Symbol
Graph	$\mathcal{G} = (V, E)$ with V a finite set and $E \subseteq V \times V$	$\mathcal{G}$
Directed edge	$(v_i, v_j) \in E \wedge (v_j, v_i) \notin E$	$v_i \rightarrow v_j$
Undirected edge	$(v_i, v_j) \in E \wedge (v_j, v_i) \in E$	$v_i \sim v_j$
Directed graph	Graph where all edges are directed	
Undirected graph	Graph where all edges are undirected	
Parent node	$v_i \rightarrow v_j$	$v_i \in pa(v_j)$
Child node	$v_i \rightarrow v_j$	$v_j \in ch(v_i)$
Family	$\{v_i\} \cup pa(v_i)$	$fa(v_i)$
Neighbor node	$v_i \sim v_j$	$v_i \in ne(v_j) \wedge v_j \in ne(v_i)$
Adjacent node in a directed graph	$v_i \rightarrow v_j$	$v_j \in adj(v_i)$

Item	Definition	Symbol
Adjacent nodes in an undirected graph	$v_i \sim v_j$	$v_i \in adj(v_j) \wedge v_j \in adj(v_i)$
Subgraph of a graph	$\mathcal{G}_A = (A, E_A)$ with $A \in V$ and $E_A \subseteq E \cap A \times A$	$\mathcal{G}_A$
Complete graph	$\forall (v_i, v_j) \in V$, $\exists \mathrm{v}_i \rightarrow v_j \vee v_j \rightarrow v_i$	
Cliques of a graph	Maximal complete subgraphs	
Path	Sequence $v_i = v_0, v_1, ..., v_n = v_j$, s.t. $(v_{k-1}, v_k) \in E \;\forall\; k = 1, ..., n$	$v_i \mapsto v_j$
Directed path	Path s.t. $\exists v_{k-1} \rightarrow v_k$ for at least one $k \in \{1, ..., n\}$	
Cycle	Sequence $v_i = v_0, v_1, ..., v_n = v_i$, s.t. $(v_{k-1}, v_k) \in E \;\forall\; k = 1, ..., n$	
Directed cycle	Directed path s.t. $v_i = v_j$	
Acyclic graph	Graph which does not contain any cycles	
Directed acyclic graph (DAG)	Directed graph which is acyclic	$\mathcal{D}$

(Table continued from previous page)

A *graph* is defined as a pair $\mathcal{G} = (V, E)$, with V a finite set and $E \subseteq V \times V$. V is a set of vertices, also called nodes, and E the set of edges or links of the graph, given as a set of ordered pairs of vertices. An edge between two vertices v_i and v_j is *undirected*, written $v_i \sim v_j$, if $(v_i, v_j) \in E \wedge (v_j, v_i) \in E$. An edge between v_i and v_j is *directed*, written $v_i \rightarrow v_j$, if $(v_i, v_j) \in E \wedge (v_j, v_i) \notin E$. If all edges in a graph are directed, it is called a *directed graph*; if all edges are undirected, it is an *undirected graph*.

If there is a directed edge $v_i \rightarrow v_j$, v_i is a parent of v_j $(v_i \in pa(v_j))$ and reciprocally, v_j is a child of v_i $(v_j \in ch(v_i))$. The family of a vertex v_i is defined as $fa(v_i) = \{v_i\} \cup pa(v_i)$.

If there is an undirected edge between v_i and v_j, we say that v_i and v_j are *neighbors*. The neighbor relation is symmetric, such that $v_i \in ne(v_j)$ and $v_j \in ne(v_i)$.

For undirected graphs, *adjacent* nodes are neighbor nodes. In a directed graph, v_j is adjacent to v_i, $v_j \in adj(v_i)$, if there is an edge $v_i \rightarrow v_j$, i.e., if

$v_j \in ch(v_i)$ (Neapolitan 1990, p.97).

A *subgraph* of $\mathcal{G}$ is defined as a graph $\mathcal{G}_A = (A, E_A)$ with $A \in V$ and $E_A \subseteq E \cap A \times A$. A graph $\mathcal{G}$ is *complete* if there is a link between every pair of vertices, i.e., if $\forall (v_i, v_j) \in V, \exists \mathrm{v}_i \rightarrow v_j \vee v_j \rightarrow v_i$. The maximal complete subgraphs of $\mathcal{G}$ are called its *cliques*.

A *path* from v_i to v_j (written $v_i \mapsto v_j$) is a sequence $v_i = v_0, v_1, ..., v_n = v_j$ of distinct vertices such that $(v_{k-1}, v_k) \in E \; \forall \; k = 1, ..., n$. A path is a *directed* path if there is a directed edge $v_{k-1} \rightarrow v_k$ for at least one $k \in \{1, ..., n\}$. A path can not cross itself and never makes use of movement against the direction of arrows. Additionally, a directed path includes at least one step in the direction of an edge. Cycles are paths which return to their starting points: A *(directed) cycle* is a (directed) path where the end points are identical, i.e., $v_i = v_0, v_1, ..., v_n = v_i$. If there are no cycles in a graph, it is called *acyclic*. Based on the above definitions, we can now define a *directed acyclic graph* (DAG) as a directed graph which is acyclic.[8]

Starting from an original graph $\mathcal{G}$, its *undirected version* $\mathcal{G}'$ can be constructed by replacing all directed edges by undirected ones. If in $\mathcal{G}'$, there is a path between any pair of vertices (v_i, v_j), the graph $\mathcal{G}'$ is *connected*. If, furthermore, $\mathcal{G}'$ contains no cycles, it is called a *tree*. In a tree, there exists a unique path between any two vertices. Thus trees are *singly connected* networks, i.e., networks where at most one undirected path exists between any two vertices. *Multiply connected* networks are such that more than one path exists between at least one pair of vertices (v_i, v_j). In practice, BBN are usually multiply connected.

2.4.3 Definition of Bayesian Belief Networks

As pointed out earlier, BBN consist of two elements, namely a graphical and a probability model. Cowell et al. (1999, p.5) say that " 'Bayesian Networks' can be formed by superimposing a probability model on a graph representing qualitative conditional independence assumptions." The two elements will be described in the next paragraphs.

2.4.3.1 The Graph

Jensen (1996, p.18) defines the graph of a Bayesian Network as consisting of a set of variables with a finite set of mutually exclusive states for each, and a

[8] As a directed graph only contains directed edges by definition, it can only contain directed cycles. The definition of a DAG does not preclude its undirected version from containing undirected cycles.

set of directed edges between variables. Variables and edges together form a directed acyclic graph (DAG).

The DAG can be seen as a "graphical representation of *conditional independence*" (Cowell et al. 1999, p.26). A random variable X is conditionally independent of a variable Y given Z if for any possible pair of values (y, z) it holds that the distribution $D(X \mid Y = y, Z = z) = D(X \mid Z = z)$. The fact that X is conditionally independent of Y given Z can be written as $XY \mid Z$ (Cowell et al. 1999, p.64).

The concept of conditional independence is illustrated by Jensen (1996, p.8) using the example of two car drivers, Holmes and Watson, and the probabilities that each of them has an accident. There is a variable that influences this probability for both of them, namely the road conditions in the region where they are driving. However, once we know these conditions for sure, the accident probabilities for Holmes and Watson become independent of one another. Thus, they are conditionally independent, given road conditions.

The property of conditional independence is very important for drawing inferences in Bayesian Belief Networks, because it permits local computation, a property that will be dealt with lateron (see Section 2.4.4.2).

2.4.3.2 The Probability Model

The probability model superimposed on the graph consists of a joint distribution defined on its variables. Generally, the form of such a distribution depends on the structure of the graph. For a DAG, which is the form of graphs used in BBN by definition, conditional probability distributions for each node v_i given its parents have to be specified. To each variable v_i with parents $pa(v_i)$, a conditional probability table $p(v_i \mid pa(v_i))$ is attached (Jensen 1996, p.18).

The joint distribution of the set of all nodes V in the graph results as the product of conditional probability distributions,

$$P(V) = \prod_{v_i \in V} p(v_i \mid pa(v_i)). \tag{2.10}$$

In principle, if we have the joint probability distribution over V, we can calculate the probability distributions of single nodes v_i by marginalizing all variables but v_i out of $P(V)$, $P(v_i) = \sum_{V \setminus v_i} P(V)$. We could also update the probability distributions for nodes given some evidence directly on the joint distribution. However, the joint probability distribution over V grows exponentially with increasing number of variables $v_i \in V$, causing computational problems. Thus, the representation of the joint distribution in a Bayesian Belief Network is very convenient. Information on P(V) is stored in a number of conditional probability tables (CPT), from which the joint distribution can be calculated if needed (Jensen 1996, p.20). The question of how to update probabilities using CPT will be discussed in Section 2.4.4.3.

2.4.4 Developing a Bayesian Belief Network

In this section, elementary requirements and techniques for setting up a Bayesian Belief Network and drawing inferences are presented. The presentation focusses on techniques needed for the BBN presented in Chapter 4 of this thesis. It is based predominantly on Cowell et al. (1999) and Jensen (1996) which can be consulted for an in-depth treatment.

According to Cowell et al. (1999, pp.25ff), the development of a probabilistic model consists of three phases, namely:

1. Defining the model,
2. Constructing the inference engine, and
3. Using the model for case analysis.

I will follow this order in the following description.

2.4.4.1 Defining the Model

The process of defining the model, in turn, takes the following three steps (Cowell et al. 1999, p.25): According to , consists of

1. Specifying relevant variables,
2. Specifying structural dependence between variables, and
3. Assigning component probabilities to the model.

In the first step, variables that will be included in the model have to be chosen, and in a second step, their dependencies are determined. In practice, these two steps often intermingle with each other, because the person or group of persons setting up a BBN has at least parts of a structure in mind when choosing variables. For a given question, the choice of some vertices will usually be straightforward, e.g., vertices representing the event in question or other events which are expected to be important drivers of its state.

The aim of such a model is to provide probability estimates for events of interest – events the occurrence of which can not be observed, or can be observed only at prohibitive costs. Jensen (1996, pp. 34-36,61) gives the following classification of variables used in Bayesian Belief Networks for decision support, which helps getting a clearer picture of how to choose them and how to build the structure: First, the events we are interested in will be modeled as *hypothesis variables*. Second, there may be information that hints at what state a hypothesis variable is in. To use such information in the model, *information variables* are specified in a way that new findings which add evidence on what state the information variable is in can be entered. Third, further variables introduced for convenience are called *mediating variables*. There are different reasons for introducing a mediating variable. For example, the introduction of a common parent for two variables which are dependent, but neither directly nor via any of the existing variables, allows for indirect dependence. Moreover, mediating variables may ease the acquisition of conditional probabilities. For example, a technique called 'divorcing' can be applied to reduce the space of parent configurations for a node, diminishing the size of its CPT. The idea is to introduce a mediating variable which summarizes distributions of some of the parents, thus 'divorcing' them from the remaining parents (Jensen 1996, p.52). However, the number of mediating variables should be restricted. The refinement added to the model has to be carefully balanced with loss of performance due to increased complexity. The third kind of variables, mediating variables that are introduced to improve the structure of dependencies, shows that the choice of variables can not be made independently of structural considerations. For each variable, exhaustive sets of mutually exclusive possible states have to be defined.

Cowell et al. (1999, p.27) call the first two steps in the development of the graphical model, where general relationships between variables and the relevance of one to another are considered, 'qualitative modelling' . It allows a graphical representation of conditional independence to be set up without thinking about quantitative aspects or probabilistic structures. At this stage, the decision has to be made what kind of graph is constructed, e.g., a directed graph or an undirected graph. In our case, as a BBN is built, the graph has to be a directed acyclic graph, and thus only directed edges can be used. They represent probabilistic or causal influence, or, more weakly, direct relevance of one to another.

The qualitative modeling stage leads to a graph that is not necessarily linked to a probabilistic interpretation. According to Cowell et al. (1999, pp.28f), 'probabilistic modelling', or 'quantitative modelling', constitutes the next stage. It connects the graph to a joint probability distribution defined on its variables.

As described in Section 2.4.3, the joint probability of variables in a BBN is specified through conditional distributions for each node, given any configuration of its parents.[9] When all nodes take discrete values, conditional distributions can be specified by filling in a conditional probability table (CPT) for each node.

Probabilities to feed into a model's CPT can come from different sources, as well as from combinations thereof. Jensen (1996, pp.38ff) lists three possible sources for acquiring conditional probabilities, namely

- theoretical foundation,
- frequencies, e.g., from cases in a data base, and
- subjective estimates.

For the purposes of the present BBN, probabilities will be provided through expert elicitation. Each expert is asked to specify a complete joint distribution. The elicitation of probabilities will be discussed in detail in Sections 2.5.2ff.

2.4.4.2 Constructing the Inference Engine

We want to use our BBN for updating probabilities in the light of new evidence. When we get some information on the state of a node of our BBN, we want to be able to insert this finding into the network, and we want the network to propagate the new knowledge in a way that conditional probabilities throughout the whole network are updated to the new state of knowledge.

Exact inference in Bayesian Belief Networks is relatively easy for singly connected networks, i.e., networks where at most one undirected path exists between any two variables. In that case, there is a unique way of passing knowledge entered at one node on to other nodes.

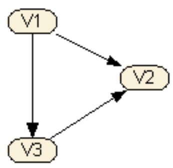


Figure 2.4: An Example BBN

[9] The form of this distribution depends on the structure of the graph. For an undirected graph, e.g., a potential function has to be specified for each of its cliques, such that the product of potential functions over all cliques yields the overall joint density (Cowell et al. 1999, p.28).

For multiply connected networks, however, the complexity of computation increases.[10] In that case, there is more than one way to propagate information entered at one node to another one. In the network displayed in Figure 2.4, e.g., evidence entered at node v_1 can be passed on to node v_3 in two ways. First and obviously, it can be passed on via the direct link, as for the children of any node v_i, a conditional probability distribution $p(ch(v_i) \mid v_i)$ is stored, which will change when the distribution of v_i changes. Second, knowledge propagation may also take place in the opposite direction of directed edges, in this case indirectly from v_1 via v_2 to v_3, against the direction of the edge $v_3 \rightarrow v_2$, given that v_2 is not instantiated. Thus, information on v_i may tell us something on the distribution of its parents $pa(v_i)$, as well. This is due to the symmetry in Bayes' Rule, which allows us to learn something on $p(pa(v_i) \mid v_i)$ from $p(v_i \mid pa(v_i))$. Taking another look at Figure 2.4, this means that, e.g., evidence entered at v_3 can be passed on to v_1, as well as to v_2 and then v_1 against the direction of the edge $v_1 \rightarrow v_2$, given that none of the two nodes is instantiated. Intuitively, e.g., we would think that causes of a certain illness become more likely to have been present once we learn that the illness has occurred. The existence of (undirected) cycles in the undirected version of a network's DAG makes knowledge propagation a non-trivial exercise. Moreover, the calculation of conditional probabilities becomes computationally more demanding with increasing state space of the variables.

In principle, it is possible to use the joint probability distribution stored in the network as the product of all conditional probability tables to update probabilities given some evidence e. To this purpose, the multiplication rule (given in Equation 2.2) can be applied:

$$P(v_i \mid e) = \frac{P(v_i \cap e)}{P(e)} = \frac{P(v_i \cap e)}{\sum_{v_i} P(v_i \cap e)}$$

If the evidence is that a node v_k in a node set V is instantiated in state v'_k, calculating the new probability distribution for a variable v_j, $P(v_j \mid v'_k)$, consists of the following steps:

1. Computing the probability of any configuration of all variables in V.
2. Then, for any value v_j may take, summing the probabilities calculated in 1) over all configurations for which v_j takes that value and $v_k = v'_k$ (i.e., calculating $P(v_j \cap v'_k)$ for any v_j).

[10] Solutions to intractably large multiply connected networks can be found using approximate inference techniques, e.g., Monte Carlo algorithms and sampling. Such techniques are not subject of the present thesis.

3. Summing the probabilities calculated in 2) over all configurations of v_j (computing $\sum_{v_j} P(v_j \cap v'_k)$).

4. Calculating the ratio of 3) over 4), (i.e., $\frac{P(v_j \cap v'_k)}{\sum_{v_j} P(v_j \cap v'_k)}$) for any v_j.

For updating the whole network, this procedure has to be executed for any variable in V the probability distribution of which is affected by the new knowledge on v_k. Although this is a clear task that a computer can fulfill, in principle, it can be computationally demanding, as the network's state space increases exponentially with an increasing number of variables. For example, if each variable has three possible states, five variables have $3^5 = 243$ configurations, and twenty variables already have 3^{20}, i.e., approximately 3.5 billion possible configurations. Such processes can easily reach the limits of computational power (Spiegelhalter et al. 1993, p.225). In a BBN model, the joint distribution is stored in the (conditional) probability tables for each variable, and can be built from these local relationships. For computational purposes, a BBN can be broken down into smaller subgroups, which Spiegelhalter et al. (1993) denote as *belief universes*. The above calculations can then be performed in the subgroups, which makes computation much easier, and belief universes communicate with each other. Spiegelhalter et al. (1993, p.225) call this a strategy of 'divide and conquer'.

The restructuring of a network can be performed by BBN software. During the compilation process, the original network is transformed into a structure which can be handled more easily, computationally. It is not always simple to identify suitable subgroups within a BBN, nor is there necessarily a unique way for doing it. However, once a network is compiled, all further computations can use the compiled structure for fast inference.

The BBN presented in Chapter 4 of this thesis has been implemented using the software Netica. Therefore, in the following it will be described how Netica proceeds when building an inference engine for a BBN. The process is similar to mechanisms used by other software.

When compiling a Bayesian Belief Network, Netica constructs a junction tree (also called join tree) of cliques of the original nodes in the network. Nodes are clustered in a way that a singly connected network of node clusters results which is probabilistically equivalent to the original network. When findings are entered into the original network, updating is performed on the underlying junction tree, using a message-passing algorithm (Norsys Software Corp. 1996, p.18). Therefore, the junction tree can also be referred to as the 'inference engine' of a network.

The junction tree to be constructed from the original directed acyclic graph has the following properties: Its nodes are sets of nodes of the original DAG, so-called *cliques*. Links between the cliques are labelled with *separators*. The separator of two adjacent cliques c_i and c_j consists of $c_i \cap c_j$. Cliques and separators hold tables specifying the configuration of their variable sets. For each pair of cliques of a junction tree c_i, c_j, all cliques on the path between them contain $c_i \cap c_j$. A junction tree representing a Bayesian Belief Network over the variable set V has the following two properties (Jensen 1996, pp.72, 81):

- For each variable v_i, the junction tree contains a clique c_i such that $pa(v_i) \cup \{v_i\} \subseteq c_i$.
- The joint probability distribution of the network $P(V)$ is the product of all clique tables divided by all separator tables.

According to Cowell et al. (1999, p.25), the construction of the inference engine comprises the following steps:

1. Moralizing the graphical model,
2. Triangulating the moral graph,
3. Finding the cliques of the moral graph, and
4. Making a junction tree from the cliques.

Netica compilation is not publicly documented, but in the Netica User Guide, advice is given to read Spiegelhalter et al. (1993) and Neapolitan (1990) for the algorithms Netica uses for inference (Norsys Software Corp. 1996, pp.15f). Therefore, although I can not describe the exact Netica algorithm, it is likely to be similar to the following explanation which is based on Spiegelhalter et al. (1993). They subsume steps 2 throughout 4 as the 'identification and organisation of belief universes' (Spiegelhalter et al. 1993, p.236).

First, a so-called *moral graph* is constructed from the DAG $\mathcal{D}$. This is done by adding undirected edges between all parents of a common child in $\mathcal{D}$ ('marrying parents'), and dropping the directions of all edges (Spiegelhalter et al. 1993, p.235). The authors call the moral graph resulting from the described procedure $\mathcal{D}^m$.

In analogy to the joint probability distribution $P(V)$ over all variables in a graph $\mathcal{D}$ given in Equation 2.10, the joint distribution of $\mathcal{D}^m$ is given as a product defined on the cliques of the graph, i.e., on the maximal sets of nodes all linked to each other. If cliques of $\mathcal{D}^m$ are chosen to be the families of $\mathcal{D}$, $fa(v_i)$, this condition is fulfilled, and the joint density $p(V)$ can be expressed as

$$p(V) = \prod_{v_i \in V} f(fa(v_i)), \tag{2.11}$$

where f is a function defined on $fa(v_i)$ (Spiegelhalter et al. 1993, p.235).

The joint distribution $p(V)$ is *Markov* with respect to the moralized graph $\mathcal{D}^m$ in the following sense: If $A, B, C \in V$ are sets of nodes such that any path in $\mathcal{D}^m$ from a node in A to one in B must pass through C, then $A \perp\!\!\!\perp B \mid C$, where $\perp\!\!\!\perp$ signifies independence (modified from Spiegelhalter et al. 1993, p.235). Still further conditional independencies can be revealed when using ancestral sets $W \in V$, i.e., sets which contain their own ancestors. According to Spiegelhalter et al. (1993, p.236), "this technique of forming the moral graph of ancestral sets will reveal *all* the conditional independence properties logically implied by $p(V)$ being recursive with respect to $\mathcal{D}$." Using the representation of $p(V)$ over the moral graph $\mathcal{D}^m$, some conditional independencies shown in the original graph $\mathcal{D}$ are no longer visible, but hidden in the quantitative model component (Spiegelhalter et al. 1993, p.236).

The aim of compilation is to organize the set of cliques $\mathcal{C}$ of a graph into a tree, the so-called *junction tree* $\mathcal{J}$, where for any node $v_i \in V$, the collection of all cliques $c_i \in \mathcal{C}$ which contain v_i forms a sub-tree of $\mathcal{J}$. It has been shown that this can be done if and only if the graph is *triangulated* (Spiegelhalter et al. 1993, p.236). A triangulated graph (also called *chordal*) is a graph where any cycle of length > 3 has a chord. The moral graph $\mathcal{D}^m$ we have constructed so far may or may not be triangulated. If it is not, we have to construct an extended graph $\mathcal{D}^m_+$ by adding further edges to $\mathcal{D}^m$ in a suitable way. The joint density on $\mathcal{D}^m$ given in Equation 2.11 will be Markov on any extended graph $\mathcal{D}^m_+$ over V, but further conditional independencies become invisible in the graphical structure and implicit in the quantitative model (Spiegelhalter et al. 1993, pp.236f).

According to Jensen (1996, p.86), the triangulation is the only problematic step on the way from DAG to junction trees. This is the case because triangulation is not unique, and the choice of a triangulation will determine the size of cliques and of their probability tables, and thus the computational complexity. Ideally, the cliques of the triangulated graph should have state spaces as small as possible. Different choices of triangulation will not change propagation outcomes, but can largely influence the effort needed to perform it. However, there is no general solution to choosing an optimal triangulation.[11]

[11]Determining an optimal triangulation is an $\mathcal{NP}$-complete problem (Spiegelhalter et al.

Jensen (1996, p.84) proposes that *elimination* can be used to determine whether the graph already is triangulated, and to triangulate it by adding further undirected edges if necessary. A node v_i is eliminated by adding links between its neighbors such that all neighbors are pairwise linked, and then removing v_i and its links. To this purpose, an *elimination order* has to be defined, i.e., some order in which all nodes can be eliminated one-by-one. This order will lead to a certain triangulation. Netica reports the elimination order for a network once it has been compiled, but there is no description of how the order is chosen.

Spiegelhalter et al. (1993, p.237) suggest *maximum cardinality search* as a simple algorithm for checking whether a graph is triangulated and if it is, building a junction tree. All nodes in a graph get a label $i = 1, ..., n$ by the following procedure. In a first stage, an arbitrarily selected node in V is labelled '1'. Then, in consecutive stages, the labels $i = 2, 3, ..., n$ are given to the nodes with the largest number of labelled neighbors, respectively. When several nodes have the same (largest) number of labelled neighbors, one of them is chosen arbitrarily. A stage is *successful* if all labelled neighbors of the node v_i which gets a label in that stage are neighbors of each other. If and only if the graph is triangulated, all stages are successful. If all n stages have been successful, their labeling is a so-called *perfect numbering*, where for any node, all neighbors having a lower number are connected. The algorithm guarantees that labeling of one clique is completed before proceeding to the next one. Identifying the cliques of a triangulated graph is trivial, as they are the maximal sets of variables which are all pairwise linked (Jensen 1996, p.81). The cliques of the graph are the nodes of the junction tree (Jensen 1996, p.91).

The numbering can be used to derive an ordering of cliques. The highest label within each clique c_j is noted, and cliques are then numbered $c_1, c_2, ..., c_n$, starting from c_1 for the clique with the lowest noted label to c_n for the clique with the highest noted label. The ordering is now used to assign links between the cliques such that the *running intersection property* is fulfilled, i.e., all cliques on the path between two cliques have to contain their intersection. Let $s_j = c_j \cap \{c_1, ...c_{j-1}\}$, $j = 1, ..., n$, i.e., s_j is the intersection between the nodes in c_j and the nodes in all cliques with lower numbers. Then, $s_j \subseteq c_k$ for at least one $k = 1, .., j-1$, which means that at least one clique c_k contains the intersection s_j. The tree is constructed by placing a link between (one of the) c_k and c_j for any $j = 1, ..., n$. In the tree, evidence can then be passed on a unique path (Spiegelhalter et al. 1993, p.237).

1993, p.236).

Once the graphical structure of the junction tree has been determined, the tree has to be initialized. This means it has to be made sure that the junction tree holds a probabilistic model representing the joint probability distribution of the original network. This can be done as follows.

By definition, for any node v_i, at least one clique c_i exists such that $fa(v_i) \subseteq c_i$. For each variable v_i, one c_i fulfilling this condition is chosen and v_i is assigned to it. For each clique $c_i \in \mathcal{C}$, a function $a_{c_i}(c_i)$ is defined as follows (Spiegelhalter et al. 1993, p.237):

$$a_{c_i}(c_i) = \begin{cases} \prod_{v_i} p(v_i \mid pa(v_i)), & \forall\ v_i \text{ assigned to } c_i \\ 1, & \text{if no } v_i \text{ is assigned to } c_i. \end{cases} \tag{2.12}$$

Equation 2.11 is then transformed to

$$p(V) = \prod_{c_i \in \mathcal{C}} a_{c_i}(c_i). \tag{2.13}$$

Spiegelhalter et al. (1993, p.238) propose to further generalize the expression in order to allow for more freedom. To this aim, a family $\mathcal{S}$ of *separators* is introduced. For any two adjacent cliques c_i and c_j of the junction tree, the separator is defined as $s_i = c_i \cap c_j$, i.e., each set of nodes of the graph is associated with the intersection between them. In analogy to the function a_{c_i} for each clique c_i, we now define a function b_{s_i} for each separator s_i, such that instead of Equation 2.13, we get

$$p(V) = \frac{\prod_{c_i \in \mathcal{C}} a_{c_i}(c_i)}{\prod_{s_i \in \mathcal{S}} b_{s_i}(s_i)}. \tag{2.14}$$

The functions a and b are so-called *potential functions*, and Equation 2.14 is a *potential representation*. Its right hand side is interpreted to be 0 when the denominator takes the value 0. The a functions are initialized as described in Equation 2.12, and the b functions as $b_{s_i} \equiv 1$ for all s_i.

Computation on the junction tree, e.g., when incorporating new evidence and propagating it, will modify the potential functions in a number of steps (see next section), but Equation 2.14 will hold at any time. After all steps have been performed, the final potential functions represent the marginal densities for their respective sets of variables. The marginal representation of p, defined by Equation 2.14, may be written as

$$p(V) = \frac{\prod_{c_i \in \mathcal{C}} p(c_i)}{\prod_{s_i \in \mathcal{S}} p(s_i)}. \tag{2.15}$$

The marginal distribution of the single nodes can be calculated from the clique marginal distributions (Spiegelhalter et al. 1993, p.238).

2.4.4.3 Incorporation and Propagation of new Evidence

Once the inference engine has been built, it can be used to carry out learning from new information within the network. This process is described in the present paragraph. Just as the construction of the inference engine, the way Netica incorporates and propagates evidence is not publicly documented. The process will, again, be described based on Spiegelhalter et al. (1993, pp.238-240). The reference has been given in the Netica manual (Norsys Software Corp. 1996), such that it can be assumed that the process described is close to the routine used within Netica.

Let's assume evidence $e : X_A = x_A^*$ is observed which indicates that one or more variables, forming a set A, are instantiated at given values, i.e., $A := \{V_i \mid x_{v_i} = x_{v_i}^*\}$. A new function p^* can be defined as follows:

$$p^*(x) = \begin{cases} p(x), & \text{if } x_A = x_A^*, \\ 0 & \text{otherwise.} \end{cases} \tag{2.16}$$

The new function p^* gives the joint distribution of x and the new evidence, $p^*(x) = p(x \cap e)$, and following the multiplication rule from Equation 2.2, $p(x \cap e) = p(e)p(x \mid e)$. The latter part, $p(. \mid e)$, is the probability density of the distribution conditional on e. Thus, p^* is proportional, but not equal to a probability density function.

Equation 2.16 can be rewritten as

$$p^* = p \prod_{v_i \in A} l(v_i), \tag{2.17}$$

where

$$l(v_i) = \begin{cases} 1, & \text{if } x_{v_i} = x_{v_i}^*, \\ 0 & \text{otherwise.} \end{cases} \tag{2.18}$$

The function $l(v_i)$ is called the *likelihood function* based on the evidence $X_{v_i} = x_{v_i}^*$ for each of the instantiated v_i.

Starting from a joint distribution for $p(V)$ as given in Equations 2.13 or 2.14, we can obtain a representation for $p^*(V)$ by assigning each $v_i \in A$ to one clique containing v_i, and replacing the $a(c_i)$ functions by

$$a(c_i) = a(c_i) \prod \{l(v_i) : v_i \text{ is assigned to } c_i\}, \tag{2.19}$$

where an empty product is interpreted as unity.

We can use p^* to calculate $p^*(c_i) = p(e)p(c_i \mid e)$ or $p^*(s_i) = p(e)p(s_i \mid e)$ for any clique c_i or separator s_i. The sum over $p^*(c_i)$ or $p^*(s_i)$ for $i = 1, ..., n$ then yields $p(e)$, the *normalizing constant*. By this means, the joint density can be calculated at specified values for any collection of variables. Moreover, by dividing $p^*(c_i)$ by $p(e)$, i.e., by performing the normalization, $p(c_i \mid e)$ can be derived for any clique such that the effect of evidence transmitted to any clique can be seen.

Once new evidence has been entered, the resulting new marginal representation is of interest. It can be calculated by propagation throughout the junction tree, departing from a potential representation. Propagation proceeds by so-called flows, each of which involves two adjacent cliques and their separator, and after each flow, Equation 2.14 holds. The process uses the fact that the information two adjacent cliques c_i and c_j have in common is the information on their separator s_{ij}. Let's assume that c_i has received evidence it is now going to propagate to c_j by the following two steps:

1. A new potential function $b^*(s_{ij})$ over s_{ij} is computed by summing out over all variables v_i in c_i that are not in s_{ij}.

2. The *update ratio* r is determined by dividing the new potential over s_{ij} by the old one, i.e., $r = \frac{b^*(s_{ij})}{b(s_{ij})}$. The new potential over c_j is calculated term by term by multiplying the old potential by the update ratio.

The above procedure is carried out to pass on information between two adjacent nodes. In order to propagate evidence throughout the whole network, flows between adjacent nodes have to be scheduled appropriately. There are different ways for constructing an order of flows, which differentiate in the mechanism applied, but not in the results obtained. Spiegelhalter et al. (1993) mention the following schemes:

- *Palindromic*: A flow is called *active* if a sender receives active flows from all its neighbors before sending a flow, with the possible exception of the one it sends to. Such a scheme starts from and ends at a peripheral clique. The palindromic schedule is constructed such that in the end, when the 'equilibrium' state is reached, an active flow has been passed in both directions beween each pair of adjacent cliques.

- *Root-clique*: This approach has been proposed by Jensen et al. (1990). A root-clique c_0 is selected arbitrarily. In the first phase, *collection*, it requests flows from all its neighbors, which in turn pass on requests to their neighbors if there are any, until the requests can be satisfied and information is propagated to c_0. That clique then has its equilibrium value, and starts the second phase, *distribution*. During this phase, flows are passed from c_0 towards the peripherie, until all cliques reach equilibrium.

- *Dynamic flow scheduling*: In principle, an established schedule of sequences can be used repeatedly for different purposes. However, this may be inefficient, e.g., if only one clique c_i receives evidence, only distribution from that clique as a root is needed. Spiegelhalter et al. (1993) therefore propose a production rule associated with each flow, such that a clique sends information when at least one incoming flow has changed, and the remaining ones are active.

From the Netica manual, it can not be concluded which propagation scheme is applied. However, knowing that any schedule will lead to the same outcome (at smaller or greater efficiency), we will contend with this description of a range of possible schemes.

2.4.4.4 Computational Limits and Approximate Inference

In the above sections, exact techniques for compiling Bayesian Belief Networks have been presented. However, exact inference can be computationally demanding (Spiegelhalter et al. 1993, p.225). As has been discussed, the efficiency of an inference engine depends on the choice of triangulation, and no general algorithm exists to detect the most efficient one. As Spiegelhalter et al. (1993, p.241) say: "With good triangulation algorithms remarkably large and dense networks can be handled, but there comes a point when computational limits are exceeded." According to the authors, this problem occurs especially when many nodes represent parameters which are linked to many other nodes, or when the graphical structure shows some form of regularity, e.g., in complex temporal models. The applicability of BBN can be extended if exact propagation is substituted with Monte-Carlo methods (Spiegelhalter et al. 1993, p.245).

In the conclusions of a BBN textbook which presents some 20 different applications, Patrick Naim points out that: "Computational complexity is one of the strongest limitations of Bayesian networks."(Pourret et al. 2008, p.384) The problem is persistent, as BBN algorithms are of nonpolynomial complexity, thus computation time grows exponentially with increasing network complexity. Network complexity, in turn, does not depend so much on the number of nodes, but on the connectivity of the network. Naim adds that computational limits would generally not pose a problem in expert-based models, because the knowledge elicited from respondents would limit networks to computable sizes.

This is in contrast to the experience I have made with processing an expert-based network (see Chapter 4). Once all nodes were added, the software Netica was unable to construct an inference engine and perform exact updating. In order to carry out computations on the complete BBN, I used a sampling update function that was added by Netica personnel on request. Instead of establishing an inference engine that can be used for all subsequent updating steps, the approximate inference function draws samples from the distributions underlying the nodes.

The problems I faced may be due to the fact that all elicitation nodes within the BBN contain (discretized) continuous probability distributions. Sigurdsson et al. (2001, p.189) find that a major drawback in constructing BBN was the fact that currently available BBN software had limited capability to process continuous variables, which therefore needed to be discretized. In their overview on the use of BBN in system reliability modeling, they say: "Exact propagation is feasible for relatively small networks of discrete variables but approximate algorithms have been developed and are used for larger networks and continuous variables."(Sigurdsson et al. 2001, p.182) They point out that the development of computational algorithms was currently one of the main research strands associated with BBN.

2.4.5 What is 'Bayesian' about Bayesian Belief Networks?

In Section 2.2, the two-fold use of the term 'Bayesian' has been discussed – on the one hand referring to the application of Bayes' Rule, on the other hand to the subjectivist school of thought that has formed around this rule. Bayesian Belief Networks are 'Bayesian' in at least the former sense of making use of Bayes' Rule, but they can also be Bayesian in both ways.

The first aspect will be discussed first. Bayes' Rule is the underlying principle used in Bayesian Belief Networks for executing knowledge propagation. It can directly be applied to BBN, where nodes contain conditional probabilities, given their parents' configuration.

In its simplest form, (see Section 2.2.2, Equation 2.4), Bayes' Rule describes how to calculate the conditional probability distribution of a node A given the configuration of node B, using A's prior probability, the likelihood of the finding B given A, and the overall probability of B. If we learn what state a node B is in, we can use this rule to update our knowledge on A. As the rule is symmetric, it can be used in both directions – evidence about a parent node tells us something about its child nodes, but evidence concerning a child can also be used to update our beliefs about its parents. Therefore, Jensen (1996, p.9) says that Bayes' Rule can be used to invert causal statements. The author provides examples of how to perform this computation for small, singly connected networks (Jensen 1996, pp.24ff).

The symmetry property is very useful for practical purposes. Howard & Matheson (2005, p.133) describe that it facilitates, e.g., expert elicitation of conditional probabilities. Conditional influences can be set up in such a way that the expert can supply conditional probabilities at greatest ease. The order of conditioning can then be changed by applying Bayes' Rule.

In larger, multiply connected networks, applying Bayes' Rule to any two nodes which are linked becomes a complex and sometimes intractably large operation. Therefore, "efficient methods of implementing Bayes' theorem form the inference engine used to draw conclusions on the basis of possibly fragmentary evidence."(Cowell et al. 1999, p.21) The construction of the inference engine has been the subject of the previous section.

The subjective aspect of BBN is the second aspect that needs to be discussed here. Cowell et al. (1999, p.5) stress that both subjective probability and Bayes' Rule are core ingredients of probabilistic networks: "We then focus on the probabilistic representation of uncertainty, emphasizing both its strong theoretical basis and its possibility of a subjective interpretation. Bayes' theorem then forms the fundamental tool for belief revision".

As I have argued earlier, one of the advantages of BBN is that knowledge from different sources can be incorporated, including data, but also the assessments of experts. Especially in cases where no or little data is available, but knowledge exists in the form of expert assessments, BBN are a versatile tool for making such knowledge explicit. Subjective, knowledge-based inputs into a BBN are possible at different modelling stages, e.g., when choosing variables to be taken into account, when determining the structure of the graph by adding edges, or when assigning an initial probability distribution. The doubt an expert may have about her own judgement can be reflected in the (conditional) probabilities she assigns to the values a variable can take, or in an own overall assessment of the reliability of her model. The doubt a decision-maker may have in the competence of an expert can be reflected in the degree of trust she puts into that experts' model, or in a weighting of different experts' models, where available. She could also use the model to enter own findings or adapt conditional probabilities as she considers appropriate.

The definition of probability as an individual degree of belief, which relates to the practice of specifying a BBN's probabilistic model by help of expert elicitation, goes back to the subjectivist Bayesian school. A subjectively specified BBN can therefore be considered Bayesian in two regards and the name Bayesian *Belief* Network can be interpreted to make reference to the underlying concept of subjective probability. I will use exactly this concept, and the term Bayesian Belief Network is used throughout the thesis to remind of this fact.

2.5 Expert Interviews and Elicitation

Expert interviews and elicitation are ways to reveal an expert's subjective assessment of a situation or the probability of an event. In this sense, techniques for asking experts are part of a Bayesian toolkit, and that is why they are included in this chapter on Bayesian concepts and methods.

The present investigation relies on the input of experts in different ways. Chapter 3 presents the results of a series of qualitative expert interviews, and the Bayesian Belief Network described in Chapter 4 builds on these results and has been quantified by expert elicitation. In the following, the methods used for interviewing experts are presented, and some of their problems and advantages are discussed. To avoid conceptual confusion, in the following, the term 'interviews' refers to qualitative expert interviews, and the term '(expert) elicitation' denotes asking experts to quantify subjective probabilities. The focus of this section is strongly on elicitation, as it is more critical in two regards. First, the elicitation of probabilities is more prone to systematic bias than qualitative interviews are. Second, its results were not checked and reapproved in a subsequent round of interviews or elicitation, which is true for the results of the first round of qualitative interviews, which have shaped the structure of the BBN.

Before introducing methods for interviewing and eliciting experts, however, the question arises who is an expert. In the following, some definitions are contrasted, which originate from the literature on expert interviews and elicitation summarized in the latter paragraphs of this section.

Kadane & Wolfson (1998, p.3) give the operational definition of experts in a particular context being persons about whom "it is reasonable to hope that they will have thought harder, and over a longer period of time, about the subject at hand than others have."

According to Meuser & Nagel (1991, p.444), an expert is a person who has responsibility for the drafting, implementation or control of a solution to a problem, or who has privileged access to information on groups of persons or decision processes. They point out that being an expert is a relational state, which is in some sense granted by the researcher.

Garthwaite et al. (2005, p.680) simply define the expert as "the person whose knowledge we want to elicit", thus not necessarily someone who possesses or is attributed special knowledge. When eliciting acknowledged experts, they caution that their expertise may be linked to bias, as they may have personal interest in the outcomes of elicitation. The three statements just given share the sense that the status of being an expert is relative to the subject of interest, as well as to the fact that the researcher estimates the respective interviewees' knowledge as relevant.

In the context of probability elicitation, apart from substantive knowledge of a subject area, some authors extend the criteria of their choice of experts to normative knowledge on probabilities. Renooij (2001, p.258) says: "Ideally, for probability elicitation, an expert should be selected who has the necessary domain knowledge and is familiar with assessing probabilities."

Similarly, apart from requiring experts to have encompassing knowledge of a subject matter, O'Hagan et al. (2006) point out that expertise relates to special ways of organizing and using knowledge. For successful elicitation, they require that the expert should be apt to provide judgement under uncertainty and represent her uncertainty (O'Hagan et al. 2006, p.27).

In the two rounds of elicitation conducted in the framework of this Ph.D. thesis, experts have been chosen according to their (expected) substantive knowledge. The consideration of their ability to provide probabilistic estimates has not played a role (and, fortunately, not posed any major problems).

The following sections will deal with qualitative expert interviews and then with different aspects of elicitation, including biases that may occur and problems with the aggregation of expert opinion. Consecutive sections then turn to the elicitation of probability distributions, discuss the example of eliciting dependencies in uncertain climatic processes, and describe experiences with and gives instructions for eliciting conditional probabilities for BBN.

2.5.1 Qualitative Expert Interviews

The advantages of qualitative research over other approaches are that it is more open, gets the researcher closer to the interviewee, and generally provides a more concrete and plastic image of the respondent's view (Flick et al. 2000, p.17). Social science literature provides extensive material on methods for preparing, conducting and evaluating interviews. In qualitative science, approaches can be differentiated according to in how far the structure of the interview is predetermined. Interviews can have any degree of structure, from open, non-standardised interviews (e.g., narrative interviews), which are similar to a normal conversation, to fully standardized interviews, where the order and wording of questions is fixed in an interview guideline. Different types of interviews are appropriate for different purposes, e.g., focussed interviews can be conducted for gathering the reaction to or interpretation of a given document, film, or situation, and biographic interviews are employed for opening up the story of someone's life. In practice, elements of different methods are often combined.

For a broad introduction to qualitative research, see Flick et al. (2000). The author points out that in practice, many qualitative methods require much time for data collection, transcription, and evaluation (Flick 2000, p.262), methods of which can not be fully discussed here. Financial and time constraints do not always allow fulfilling these requirements. Therefore, a number of so-called short cut strategies exist, which reduce the maximum requirements of exactness and completeness and introduce more pragmatic approaches (Flick 2000, p.262). In the case of expert interviews, limited availability of the respondents suggests using such short cut approaches.

In the literature, expert interviews are treated as a type of interview of their own. Meuser & Nagel (1991) recommend using open guidelines for expert interviews, as do Glaeser & Laudel (2004, p.107). Meuser & Nagel (1991) argue that during the development of the guideline, the researcher acquires sufficient knowledge to be a competent dialog partner for the expert. The guideline itself allows the expert considerable freedom to make her statements, while guaranteeing that the conversation does not wander from the subject (Meuser & Nagel 1991, p.448). Conducting the interview along the guideline also insures that interviews with different experts will be comparable (Meuser & Nagel 1991, p.453).

Different approaches exist for evaluating qualitative interviews, e.g., coding, qualitative analysis, narrative analysis, or hermeneutic procedures. For an overview, see Flick et al. (2000, p.262). However, expert interviews may require special treatment. Meuser & Nagel (1991) point out that rigorous methods for expert interviews, especially for their evaluation, have not been developed,. Glaeser & Laudel (2004) offer a textbook which focusses on content analysis for evaluating expert interviews, and Mayring (2003) describes the technique of content analysis without focussing on expert interviews. Content analysis is a method which extracts information from texts, transforms it, and processes it independently of the original text. It was first developed in the 1920s in the US for analyzing texts from mass media (Glaeser & Laudel 2004, p.191). It requires a complete system of categories that has to be built ex ante. The interview text is then searched for relevant information, which is assigned to the categories.

In the view of Meuser & Nagel (1991, p.452), the evaluation of expert interviews consists of a comparison of the texts of different interviews. The aim is to deduce representative aspects and common points, or shared knowledge, structures of relevance, constructions of reality and interpretations. This is in contrast to interviews with non-experts, where individual cases or specialities are what is sought for.

The authors propose a procedure for the evaluation of expert interviews which consists of the following steps (Meuser & Nagel 1991, pp.455-466):

1. Transcription: The transcript does not need to be complete, but needs to cover all relevant contents. Breaks, changes of voice etc. do not need to be marked.

2. Paraphrase: The researcher writes down the experts' statements in her own words, using common sense. No selection of contents should take place at this stage.

3. Headlines: The researcher adds headlines to the passages of transcribed text, using the terminology of the experts.

4. Comparison by themes: Paragraphs from different interviews are grouped according to common themes, and headlines are unified.

5. Sociological conceptualization: Categories are formed from the common elements of the texts, based on sociological knowledge.

6. Generalizing into a theory: A systematic scheme of categories and their relations is built; the context is generalized into typologies or theories.

As a qualitative research paradigm that, if applied, influences all steps of research, grounded theory needs to be mentioned here. Grounded theory was established by Barney Glaser and Anselm Strauss. The basic idea of this method is that theoretical concepts are discovered by analyzing data, and need to prove their worth in the light of data. Data collection and analysis are not seen as two distinct steps in the research process. Instead, available data is coded, and concepts and theories are derived at the same time at which new data is collected, which is used for reassessing the validity of previous findings. The research process is therefore both triadic (data collection, coding, and writing memos) and circular, as the researcher always returns back to data (Hildenbrand 2000). For an introduction to grounded theory, see Glaser & Strauss (1979); for a textbook, Strauss & Corbin (1996).

In the framework of this thesis, qualitative expert interviews were carried out to derive an assessment of technology available for reducing CO_2 emissions from cars, its development, and potentials, and to find out in how far such assessments diverge over different experts. An open guideline was prepared, which delineated the subjects of interest to the investigation, but allowed for flexibility in regard to the phrasing of questions, the order in which they were posed, and possible additional questions to further expand on certain points. Evaluation proceeded roughly along the lines proposed by Meuser & Nagel

(1991) as sketched above. Interviews were recorded and (fully) transcribed, and relevant passages were roughly paraphrased. As the aim of the interview series was not to deduce a theory, but to compare technology assessments, steps 2 throughout 4 of the above list were carried out by sorting paraphrased statements into tables which allowed for an easier comparison of the assessments of the different experts. The latter two steps were left out.

The whole analysis was carried out in the style of grounded theory. Data analysis was not left until all interviews were done, but was performed in a circular process, for the first two interviews, then after five more interviews had been done, and finally again for the whole set of fifteen interviews. Insights gained in previous steps were used as inputs to later processes. For a description of the interviews and their results, see Chapter 3.

2.5.2 Elicitation of Probabilities in a Bayesian Framework

The remainder of this section deals with methods, problems, and examples of expert elicitation. In contrast to the qualitative methods just discussed, expert elicitation is performed through a structured approach, and aims at quantitative assessments. As Stiber et al. (1999, p.3014) put it, “An elicitation is a structured interview used to acquire knowledge (often probabilistic) from expert subjects”. Garthwaite et al. (2005, p.680) say that: “Elicitation is the process of formulating a person’s knowledge and beliefs about one or more uncertain quantities into a (joint) probability distribution for those quantities.” The goal of gathering probability assessments is inherent to all elicitation applications I have seen, thus in the following, elicitation will always be used to denote the attempt to make the respondent reveal probabilities.

Elicitation has been used in numerous case studies in the recent past. It has been applied in areas as diverse as medicine, the nuclear industry, veterinary science, agriculture, meteorology and business studies. O‘Hagan et al. (2006, pp.193-214) have dedicated a whole chapter to the description and enumeration of elicitation studies. As they point out, in practical applications of expert elicitation, the judgements elicited are always personal (or subjective) probabilities (O‘Hagan et al. 2006, p.13).

Probabilities elicited from experts can stand for themselves, but they can also be used as an input for Bayesian approaches. This fact makes expert elicitation an invaluable tool for Bayesians. For example, O‘Hagan et al. (2006, p.9) acknowledge the vital role elicitation plays in Bayesian statistics, where it can be used for revealing prior information, e.g., to derive prior distributions, which is especially valuable when data is scarce. Kadane & Wolfson (1998, p.3) also suggest using elicitation for obtaining prior information in a Finetti–Savage view of statistics.

The reason why elicitation is especially warranted in this perspective is that, while (the dynamical version of) Bayes' Rule describes how to update given priors to new data, it does not provide information on how to generate the prior distribution. Thus, experts' assessment are a prime source for information on possible hypotheses and their initial weights. In the BBN approach at the core of this thesis, I have used expert elicitation for providing conditional probability tables for central variables.

2.5.3 Heuristics and Biases and the Quality of Elicitation

Making judgements under uncertainty is an everyday task in human life. In the absence of complete knowledge, people tend to make use of quickly and easily applicable rules, so-called heuristics, for making approximate assessments (O'Hagan et al. 2006, p.218). While heuristics are very helpful for coming to a conclusion in useful time, the results do not always represent uncertainty in a satisfactory way, but tend to be biased. O'Hagan et al. (2006) argue that when eliciting probabilities, the facilitator (and the participant) should be aware of the main biases, and the interview should be structured in a way that avoids such problems. Moreover, it has to be kept in mind that experts are not necessarily trained in giving probability assessments.

Seminal research on heuristics and biases has been carried out by Tversky, Kahneman and others from the 1970s on (see, e.g., the Science paper Tversky & Kahneman (1974), or the book Kahneman et al. (1982)). In their classic paper, Tversky & Kahneman (1974) have identified three heuristics, namely availability, representativeness, and anchoring-and-adjustment.

Much further research on criteria for successful elicitation has been carried out, of which Kynn (2008) offers an up-to-date overview. As the author describes, the original findings on inherent human bias have been weakened by Tversky and Kahneman themselves in subsequent papers. Heuristics and biases research has been complemented by a research program based on models of cognitive processes, results from which stress the importance of how to ask experts (and not only what to ask) (Kynn 2008, p.240). The author regrets that findings from this research strand of psychology have barely found repercussion in the statistics literature, which currently exhibited an 'heuristics and biases bias' (Kynn 2008, p.239). The author argues that when taking psychologic factors into account, much better elicitation results can be achieved than proposed by the heuristics and biases literature, and derives a list of recommendations which should be respected for relatively unbiased elicitation (Kynn 2008, p.260).

Furthermore, critics of the approach argue that the classic heuristics are defined in an imprecise way, and biases attributed to them have not been explained or formally proven (O'Hagan et al. 2006, p.52). Still, O'Hagan et al. (2006) find that biases occur easily, and that it is important to try to avoid them when setting up elicitation processes. For this reason, and as the heuristics and biases approach has remained very influential in statistical elicitation literature to date, the three main heuristics described by Tversky & Kahneman (1974) will be shortly presented.

- *Availability*: When using the availability heuristic, people judge the probability of an event (or the frequency of class membership) according to the ease with which such events (or instances) come to their minds. While this strategy often produces acceptable results at little effort, it is prone to some biases. For example, events with disproportionately high media coverage tend to be ascribed too high a probability because they are easily recalled. Similarly, bias may occur in regard to recent or personally important events (O'Hagan et al. 2006, pp.39f).

- *Representativeness*: This heuristic is employed for judging the probability that A belongs to some class B, or A results from a process B. The degree of correspondence (or similarity, in simple cases) of an outcome A with a model B is used as a proxy of how probable it is that A actually belongs to or results from B. When asked for an assessment of the conditional probability $P(A \mid B)$, many people intuitively use the representativeness heuristic and may arrive at faulty judgements if there are factors which do not influence representativeness, but should influence the probability assessment. As representativeness can be used for assessing probabilities of unique, non-repeatable events, this heuristic is of importance to elicitation, and its potential biases should be considered when designing elicitation procedures. O'Hagan et al. (2006) mention several biases related to representativeness which may occur in elicitation applications, namely conjunction fallacy, base rate neglect, insensitivity to sample size, confusion of the inverse, and insufficiently regressive predictions. For a description, see O'Hagan et al. (2006, pp.41-46).

- *Anchoring-and-Adjusting*: This heuristic consists in fixing an initial estimate (a so-called anchor), and then adjusting upwards or downwards. For example, when making repeated assessments of similar situations, a

> first judgement can be corrected according to the differences of further cases. However, bias occurs because people tend to make insufficient adjustments. For elicitation practice, this means that once an expert has made a quantitative statement, further statements are likely to be biased towards it, be it probabilities or assessments of observable quantities (O'Hagan et al. 2006, p.47). As an example, if a distribution is elicited and its median is specified first, experts tend to choose too narrow a range for the distribution and thus underestimate uncertainty, because their minds are anchored to the median value (O'Hagan 2009, p.85).

Apart from those linked to specific heuristics, numerous other biases have been found to exist. A contortion which may occur specifically in elicitation applications is that of a wrong level of confidence to one's assessment. Drawing on a number of calibration studies, O'Hagan et al. (2006) find that both students' and experts' estimates are often prone to overconfidence or over-extremity, in the sense of probability assessments lying too close to zero or to one. They also describe a so-called 'hard-easy effect', which means that people tend to be too confident in regard to questions where relatively many fail to provide a correct assessment, but may be under-confident in regard to simpler tasks (O'Hagan et al. 2006, pp.68-69). Morgan & Henrion (1990, p.119) describe the 'hindsight bias' as a special case of overconfidence: Participants seem to exaggerate the predictability of past events because they have trouble imagining how something else might have happened.

Interestingly, a small number of studies on lay probability forecasts suggests that overconfidence is less of a problem in regard to the assessment of probabilities of future events. O'Hagan et al. (2006, p.69) propose that for past events, participants sometimes think they remembered something which in fact was just an inference they had made, and would thus arrive at over-confident probability assessments. Forecasts, in contrast, would benefit from the absence of this effect. When it comes to assessing ranges, e.g., minimum and maximum values a variable can take, experts tend to choose too narrow a range of possible values. Therefore, it is important to encourage participants to choose as wide a range as reasonably possible (O'Hagan 2009, pp.84ff).

Another fact to consider is that elicited probabilities are the responses of participants to the questions of an interviewer, and not the revealed beliefs quantified in the experts' mind ex ante. In this sense, they are always relative (O'Hagan et al. 2006, p.218). They are sensitive to changes in language and response formats, and subject to the interpretation of the interviewer, as O'Hagan et al. (2006, p.219) point out: "The interpretation of verbal expressions varies considerably across individuals and situations. Attempts to impute specific values to them that do not take account of this are fraught with danger."

Many studies have aimed at measuring the calibration of assessors (also called external consistence), i.e., the degree to which the probabilities they attach to given events or propositions corresponds with their actual frequency of occurrence or correctness. Summing up experience from probability encoding studies, Morgan & Henrion (1990, p.128) find that calibration is rather poor, with overconfidence being the most typical flaw (see the table in Morgan & Henrion (1990, p.117) for a summary of calibration indices in different studies). These results, however, mostly refer to non-expert elicitation of almanac questions, and thus are not necessarily indicative of the success of expert elicitation in their respective area of knowledge. While it has been proposed to 'train' participants before elicitation in order to reduce bias, Morgan & Henrion (1990, p.120) point out that the effect of such measures is unclear. Kynn (2008, p.260) finds that training is valuable only when the questions directly relate to the questions of the study. It can be argued that external consistence, or calibration, is not essential to the elicitation of expert opinion, as what is to be captured is the assessment of a person, no matter how accurate her state of knowledge. As Garthwaite et al. (2005, p.680) put it: "An elicitation is done well if the distribution that is derived accurately represents the expert's knowledge, regardless of how good that knowledge is." Kadane & Wolfson (1998, p.17) say that no attempts at 'objective' calibration should be made, as "what is being elicited is *expert*, not perfect, opinions".

Therefore, Kadane & Wolfson (1998) propose that only coherence of the different statements of an expert should be checked, and the degree to which she is satisfied with elicitation outcomes. This relates to the two further aspects of consistence – apart from external consistence – which determine the quality of elicitation results: so-called internal consistence, or coherence, and self-consistence, or reliability (Kynn 2008, p.242). The latter relates to the degree to which an expert reproduces the same assessment if asked at different points in time. To check the self-consistence, Kynn (2008, p.260) suggests re-running the same elicitation with the same expert.

Kadane & Wolfson (1998, p.17) give a pragmatic definition of what is good elicitation, saying that "... the primary criterion in choosing an elicitation method is practicality. If the expert can answer the questions and feels comfortable, in the end, that to some degree her opinion has been captured, then provided that the method meets the basic mathematical criteria of coherence, and hopefully involves some reliability testing, it is a good method."

2.5.4 Aggregation of Expert Judgement

When a number of opinions from different expert are available to base a decision on, a confusing or unclear picture may arise. This section discusses how judgements can be combined or aggregated, and what are the advantages and problems related to aggregation. The question of whether aggregation is admissible at all is quite controversial. Generally, there are two ways of combining the judgements of different experts:

- Eliciting assessments from each expert, individually, and then using formal methods for combining them, and
- using group elicitation methods for fostering the convergence of assessments.

Following O'Hagan et al. (2006, p.179), these two paths are called mathematical aggregation and behavioral aggregation.

2.5.4.1 Mathematical Aggregation

O'Hagan et al. (2006, pp.180-186) present different methods for mathematically aggregating experts' judgements, e.g., Bayesian methods, opinion pooling, or Cooke's method. They conclude that: "The simple average (equal-weighted linear opinion pool) of distributions from a number of experts provides a simple, robust, general method for aggregating expert knowledge", while the (potentially better) success of more complex aggregation methods depends on a well-structured elicitation process and expert knowledge (O'Hagan et al. 2006, p.191).

Morgan & Henrion (1990, pp.166-168) also discuss different methods for combining expert judgements. The authors doubt that it is useful for policy analysis to apply sophisticated techniques for combining experts' opinions (Morgan & Henrion 1990, p.65). They argue that, when elicitation produces differences in opinion, first of all, the analyst should consider why this is the case. These differences may have been caused by, e.g., a poorly framed elicitation protocol, a doubtful choice of experts, or motivational biases (Morgan & Henrion 1990, p.164). Secondly, if the differences persist, Morgan & Henrion (1990, pp.65f) propose to carry out a sensitivity analysis in order to examine whether the disagreement among experts about a given quantity affects the overall outcome of an analysis. If not, they suggest that any reasonable scheme for combining expert opinion is admissible, e.g., equal weights. Other options are to derive weights from experts' self-ratings or ratings of each other, or to let the analyst assign weights on the basis of her knowledge. In contrast, if there is an important impact of different opinions on the results, they caution against combining experts' opinions, but recommend to communicate the different results as an important insight from the analysis.

However, even in the case of no important impact of differences in expert judgements on the overall outcome, the choice of equal weights is a pragmatic decision that has a methodical flaw. As Keith (1996, p.139) argues, "the fraction of experts who hold a given view is not proportional to the probability of that view being correct." In a paper where expert judgement is elicited, but not combined, Morgan et al. (2006, p.202) say: "Readers are reminded that we are not sampling from a distribution which describes the true value. The judgement of one of the outliners may be correct, and those who share a consensus view may be wrong. It is for this reason that we have cautioned against combining individual responses in the past, and do so as well in this case".

Formally, attaching equal weights to each expert in a sample is an 'objective' approach only if the sample is statistically representative. In practice, Keith (1996, p.141) argues, it will be impossible to elicit a large enough number of experts to guarantee representativeness at satisfactory depth. He thus opposes the idea of a "simple, seemingly objective" average expert judgement calculated by giving equal weights to experts' assessments, and concludes that the only viable option is an unequal weighting of expert opinion, brought about either explicitly by assigning weights or implicitly through the choice of experts (Keith 1996, p.142).

Apart from impracticality, Keith (1996, p.140) holds that combining elicited expert judgement is undesirable, because most audiences for which policy analysis may be intended can not make sensible use of comprehensive analytic analyses which mask their high degree of uncertainty.

2.5.4.2 Behavioral Aggregation

When elicitation produces diverging expert opinion which makes an important difference, one way of trying to reduce uncertainty is to engage experts to interact. Research in psychology has provided evidence that group interaction can foster creative problem-solving, but also that group interaction for assessing probabilities can create pressures and lead to dominance by individuals (Morgan & Henrion 1990, p.165).

There are various methods for group probability assessments. The least interactive one is the Delphi method, where participants do not meet and opinions of other experts (and possibly arguments for them) are iteratively passed over by a facilitator to foster convergence. The other extreme is a face-to-face group meeting with full discussion. Intermediate methods exist, as well.

For a discussion of the effects of these methods, see Morgan & Henrion (1990, pp.165f).

O'Hagan et al. (2006, pp.186-190) describe methods, advantages and problems of group elicitation. They find that group elicitation has greater potential to accomplish synthesis and analysis of available knowledge than mathematical aggregation, but depends strongly on the capabilities of the facilitator, who needs to avoid a number of biases known to occur in group elicitation (O'Hagan et al. 2006, p.191).

Due to the group pressures present during group elicitation, Morgan et al. (2006) fear that group elicitation may restrain the range of views discussed, and find that elicitation of single experts is more appropriate to their scientific objective: "An advantage of the method used here is that it can effectively test the range of expert judgements unhampered by social interactions, which may constrain discussion of extreme views in group-based settings"(Morgan et al. 2006, 197).

Keith (1996, p.140) generally doubts the applicability of group processes for summarizing current knowledge. If experts do not change their mind during a consensus building exercise, he argues, it is not superior to mathematical aggregation, because social persuasiveness is uncorrelated with scientific correctness of a view. And if they do, consensus building is no mere means of aggregation, but a recipe for a scientific research process.

As a result of his critique of both mathematical and behavioral methods of aggregation, Keith (1996, p.142) proposes to look for alternative modes of policy analysis instead of trying to improve methodology for combining expert opinion.[12]

As the aim of the elicitation carried out in the framework of this thesis is to provide information on the range of expert judgements and to see where they coincide or diverge strongly, experts have been elicited one-by-one, and results have been displayed alongside without aggregating them (see Chapter 4).

2.5.5 Eliciting a Probability Distribution

In this section, an example of an elicitation procedure is given. As it serves predominantly illustrative purposes, a relatively simple example is chosen, namely that of eliciting a probability distribution for a single quantity of interest provided in O'Hagan (2009). For a detailed description of more demanding applications, see, e.g., O'Hagan et al. (2006).

[12] Among the alternatives, which he calls 'punting', Keith (1996, p.140) mentions the use of scenario analysis for bounding a problem, which is roughly what is done when running different scenarios within the BBN developed as a part of this Ph.D. thesis (see Section 4.5).

O'Hagan et al. (2006, p.28) point out that there are four roles of contributors to elicitation, namely the decision-maker who needs the elicitation results, the experts whose assessments are going to be elicited, the statistician who provides expertise in methods, gives training and feedback, and the facilitator who conducts the expert interviews. Depending on the purpose of elicitation and the level of skill required, a role may be shared by several individuals, or one individual may take over more than one role. For example, in the elicitation described in Section 4.4, the author of this thesis has played the role of both the statistician and the facilitator.

O'Hagan et al. (2006, pp.28ff) describe the following preparatory steps for an elicitation: Background information is collected and evaluated, variables of interest for elicitation are identified, elicitation is planned, and the elicitation protocol is prepared. Moreover, suitable experts need to be identified and recruited.

When preparation is done, facilitator and expert meet in the case of a face-to-face procedure. Other variants are possible, e.g., telephone interviews or the use of computer-based elicitation instruments, but face-to-face interviews offer the best possibility to provide feedback to the expert and check the quality of results by the end of the interview. According to O'Hagan (2009, pp.84ff), the elicitation of a probability distribution for a quantity of interest consists of the following steps:

1. Keep a record of the elicitation process that tracks the steps of the procedure. The record should be visible to the expert who can make corrections during elicitation.

2. Record basic facts on who the experts is, what constitutes her expertise, and whether she has any competing interests in the elicitation results.

3. Perform a dummy run for giving the expert practice in the process of assessing a probability distribution.

4. Precisely define the quantity of interest.

5. Have the expert specify what evidence she builds her assessment on.

6. Ask for the range of plausible values the quantity may take, and encourage the acknowledgement of uncertainty.

7. Ask for the median of the distribution (only after its range has been specified).

8. Ask for a quantile (e.g., quartile) above and below the median, each.

9. Fit a simple distribution to the statements elicited in steps 6 throughout 8. Start with standard two-parameter distributions, and try mixtures if they do not achieve a reasonable fit. Be pragmatic, do not aim at perfect fit.

10. Feed back any deductions from the expert's statements. If she does not think that the fitted distribution represents her beliefs, go back to some of the previous steps.

11. Record final remarks from the expert.

O'Hagan et al. (2006, p.219) point out that the fitted distribution approximates the expert's statements, but implies many more statements the expert has not made. It needs carefully to be checked whether the expert finds the distribution an acceptable representation of her beliefs. As said, the present example is the relatively simple case of eliciting an univariate distribution. Eliciting multivariate probability distributions is much more demanding. When several quantities enter a probability distribution, correlation among the variables has to be considered, which complicates the issue considerably.

2.5.6 Elicitation of Dependencies in Climate Science

Expert elicitation can be used to complement scientific knowledge for providing decision support. In areas where science has not been able to achieve a reasonably complete understanding, and decisions need to be made on the basis of what is currently available, it may be warranted to elicit assessments from experts who deal with the subject in order to capture the state of knowledge plus an assessment of the degree of uncertainty it comes with. As an example, climate change and its implications are a field where many processes remain poorly understood, to date, and where expert elicitation has been used to complement the often qualitative, consensual assessments contained in the reports of the Intergovernmental Panel on Climate Change (IPCC). As Morgan et al. (2006, p.197) put it: "Expert judgement is not a substitute for definitive scientific research. Nor is it a substitute for careful deliberative review of the literature of the sort that is undertaken by the IPCC. It can, however, provide a more systematic representation of the diversity of expert judgement than is typically provided in consensus reports, and thus valuable input to the experts performing such reviews".

Scientists at Carnegie Mellon's Engineering and Public Policy Department at Pittsburgh, USA have developed rigorous methods for making experts quantify their assessments and uncertainty in regard to climate related processes and have applied them to a range of questions. Morgan & Keith (1995) have elicited probabilistic judgements about key climate variables and the nature of the climate system from 16 US-based climate experts, and Zickfeld et al. (2007) have gathered judgements of 12 climate scientists regarding the effects of global climate change on the Atlantic meridional overturning circulation. In both studies, elicitation protocols took a day of face-to-face interviewing to complete. During that process, experts were asked to, e.g., identify the most important impact variables and rank them.

In a further study, Morgan et al. (2001) have performed face-to-face interviews of 3 to 5 hours during which they elicited subjective probability distributions for biomass under a climate resulting from a doubling of the concentration of atmospheric CO_2, among others. Less time-demanding elicitation has been tried, as well. Morgan et al. (2006) describe an elicitation of expert judgements of radiative forcing from anthropogenic aerosols, based on a printed questionnaire which was completed by the experts on their own within an estimated two hours.

In many of these studies, the authors find that quantitative results derived from elicitation studies show a greater diversity of expert opinion than is apparent in the consensus summaries provided by the IPCC (e.g., Morgan & Keith 1995, Morgan et al. 2001). Consequently, Morgan et al. (2001, pp.304f) find that one virtue of quantitative elicitation is that expert judgement is framed in a transparent way, while qualitative summaries may well address differences in opinion, but mask them behind words such as 'likely' or 'unlikely' the interpretation of which differs strongly among people.

Thus, the example of climate-related elicitation studies shows that elicitation can offer more precise and more comparable results than what can be derived from (qualitative) interviews or group discussions, while revealing a larger range of uncertainty than what can be found in summaries of published literature.

2.5.7 Elicitation in the Context of BBN

Many real-world applications of Bayesian Belief Networks that have been developed in the recent past are based on elicitation. Expert inputs are used either for determining the structure of networks, providing quantification, or both. In this section, it is discussed how elicitation can be employed for these purposes, and what has to be respected.

While Morgan & Henrion (1990, p.122) doubt the ability of humans to assess covariation between different uncertain parameters correctly, they suggest eliciting marginal probabilities and conditional probabilities, instead, at least for discrete distributions. This is a very helpful recommendation as regards BBN, because they have the advantage of using a decomposition of the joint probability distribution of a set of variables into marginal and conditional probabilities as inputs, thus, exactly what can fruitfully be elicited.

Finn V. Jensen describes that when starting work on a network for medical diagnosis in the 1980s, his team underestimated the complications that would arise in two respects:

> "The task, we thought, is quite simple: determine a CPN[13] through dialogues with the experts. The rest is just mathematics and computer power. We were wrong in two ways. It is not 'just' mathematics and computer power. But even worse, to determine a CPN through dialogues with experts is much more intriguing than we anticipated." (Pourret et al. 2008, p.ix)

The first aspect, that of computational complexity of BBN, has been discussed in Section 2.4.4.4. As regards the second aspect of specifying BBN with the help of experts, elicitation, or expert's knowledge more generally, can enter BBN in two different ways. It can be used to build the structure (i.e., the graph), or for providing probabilities, namely marginal probabilities or conditional probabilities quantifying dependencies. In principle, if comprehensive data is available, both the network structure and the probabilities can be learned automatically. Unfortunately, available sources rarely provide the data needed for quantifying a BBN (Druzdzel & Van der Gaag 2000, p.481). Even where abundant probabilistic data is available, it often requires processing as well as additional knowledge about the domain in question. Thus, in many applications, expert input is needed to specify a BBN.

Many authors who have worked on BBN applications agree that eliciting the structure of a BBN, i.e., the variables and their dependencies, is much less of a challenge than eliciting the probabilities. Renooij & Witteman (1999, p.170) say that: "Constructing the qualitative part of a belief network, although elaborate, seems relatively straightforward and experts feel comfortable doing so. The quantitative part, with the probabilities over the variables, is more problematic." Druzdzel & Van der Gaag (2000, p.481) refer to obtaining the numbers as "the most daunting task in building probabilistic networks", and many others agree (e.g., Renooij & Witteman 1999, Renooij 2001, Van der Gaag et al. 1999, Van der Gaag et al. 2002).

The elicitation of probabilities for BBN is difficult due to the limited availability of experts, because "experts are reluctant to provide numerical proba-

[13] Causal Probabilistic Network, an earlier name for Bayesian Belief Network.

bilities" (Renooij & Witteman 1999, p.169), especially in cases where they are uncertain, and because of the need to obtain large numbers of probabilities. Regarding the last point, Druzdzel & Van der Gaag (2000, p.482) mention that state-of-the art networks typically consist of tens or hundreds or variables, and need hundreds or thousands of probabilities to be fully specified. They discuss how the burden of eliciting large amounts of probabilities can be reduced, e.g., whether using rough rather than accurate numbers will preserve satisfactory network behavior. They point out that the graphical structure of a network is its most important part. But although they find cases where networks have proved highly insensitive to inaccuracies in the probabilities used, which sometimes needed not be more precise than order of magnitude approximations, they draw no general conclusion but say that the accuracy required is likely to vary from case to case. They propose using sensitivity and uncertainty analysis to examine a network's behavior (Druzdzel & Van der Gaag 2000, pp.482f).

In practice, there are important effects of the qualitative structure of a network on the ease (or difficulty) with which probabilities can be elicited or calculated, and on its computational complexity. Druzdzel & Van der Gaag (2000, p.481) explain that the construction of a network "often requires a careful trade-off between the desire for a large and rich model to obtain accurate results, on the one hand, and the costs of construction and maintenance and the complexity of probabilistic inference on the other hand." For this reason, they describe network building as an iterative process which revisits the steps of identifying variables along with their possible values, depicting their relationships, and obtaining the (conditional) probabilities until a viable compromise is achieved.

2.5.7.1 Instructions for Eliciting BBN Probabilities

Renooij (2001) gives instructions which refer specifically to the elicitation of probabilities for BBN.[14] While many of the aspects important for elicitation in general, e.g., those discussed in Sections 2.5.5 or 2.5.6, are valid for the special case of BBN, as well, there are further specific demands. For example, Renooij (2001) points out that the elicitation methods available from decision analysis (e.g., Morgan & Henrion (1990)) are not necessarily appropriate for eliciting BBN probabilities, as they are too time-demanding.

[14] More precisely, she discusses methods for eliciting discrete (point) probabilities for BBN. My BBN uses elicited intervals for continuous variables, which greatly reduces the need to elicit many probabilities. Still, as much of the methods presented in that paper can be related to my work, and as it is the only methods paper I found that addresses the elicitation of conditional probabilities for BBN, a relatively detailed description is given.

Regarding the choice of experts, the elicitation of BBN probabilities may benefit from the fact that preliminary expert interviews have been carried out for determining the network structure. Renooij (2001, p.258) proposes that for eliciting probabilities, it is best to choose experts who have been involved in setting up the structure of the network. They suggest that a group of about three experts performs best, and describe an iterative elicitation process, where experts first provide an initial assessment, and a sensitivity analysis of the BBN is performed on this basis. The probabilities network results are most sensitive to can then be refined.

Compared to other elicitation approaches, the option of training experts for BBN elicitation (as well as examining calibration) is often unavailable. As Renooij (2001, p.259) puts it: "The events for which probabilities need to be assessed in a belief network are often unobservable, making feedback impossible." In fact, the very reason why expert elicitation is chosen as a means for quantifying a BBN is usually that data is biased, scarce, or simply unavailable.

For the preparation and structuring of elicitation, Renooij (2001, p.258) gives the following advice:

- Document the definitions of variables and their values, and their conditioning circumstances.
- Reduce the number of probabilities to be assessed (e.g., using fragments or disjunctive interaction).
- Prepare a question describing each event for which a probability is to be assessed.
- Prepare a question for the probability of each complementary event, as well, in order to avoid overconfidence or overestimation.
- If possible, provide a graphical format for the answers, as experience shows that experts dislike using numbers for subjective probabilities.

During elicitation, at least one elicitor has to be present, but two are preferred. The tasks of the elicitator(s) are to (Renooij 2001, p.260):

- clarify problems,
- record relevant information the expert gives apart from that required in the elicitation protocol,
- gather information on necessary changes to the network structure,
- make the expert aware of potential biases, and

- watch the clock.

The author further suggests to verify the quality of the elicited probabilities. However, she points out that it is often impossible to check whether assessments are well calibrated, i.e., conform to reality, as the respective events may be unobservable. Neither is it usually possible to check the reliability, i.e., the degree to which judgements are reproduced when doing the same elicitation over again, due to the large amount of time the elicitation requires. A check that can and should be done during elicitation is whether the probabilities are coherent in the sense of summing up to one. Moreover, the results a specified network produces under different conditioning contexts or when entering observations can be shown to the expert to see whether results match her expectations (Renooij 2001, p.260).

In the same paper, Renooij (2001) discusses possible formats for communicating with experts. While the aim is always to derive probabilities, communication can be handled in different ways, e.g., experts can be asked to provide frequencies, odds, or log-odds. Questions can be posed in mathematical notation or be verbalized, and answers can be given in words, numerically, or as marks on a scale, etc. Druzdzel & Van der Gaag (2000, p.484) argue that direct elicitation of probabilities generally is the least reliable, and graphical means like pie charts or bar graphs were easier for the experts to handle and likely to produce more accurate numbers.

Renooij (2001) also presents different indirect methods of elicitation, e.g., gambling with certainty- and lottery-equivalents, using probability wheels, and pair-wise comparisons. These methods will not be detailed here. Renooij (2001) points out that the indirect methods are quite demanding and have never been applied for large-scale application, and doubts that they would be appropriate. She argues that the choice of an elicitation method strongly depends on the ease with which it can be employed. Moreover, she suggests that some of the biases found in elicitation literature (see Section 2.5.3) may not apply to the elicitation of many probabilities for BBN. She concludes that the more elaborate methods designed to circumvent the appearance of biases may not be necessary for BBN probability elicitation.

2.5.7.2 BBN Case Studies using Elicitation and Differences of the Present Application

In this paragraph, a summary of exemplary BBN case studies is given, where elicitation has been employed to elaborate the structure of the BBN, to quantify dependencies, or both. It can then be discussed in how far the BBN presented in Chapter 4 of the present thesis contains novel elements.

In their recent textbook, Pourret et al. (2008) have assembled a range of 20 different BBN applications. On the one hand, they cover different types of applications, such as diagnosis, forecasting, classification, data mining, sensor validation and risk analysis. On the other hand, examples extend to very different questions, including medical diagnosis, crime risk factors, species conservation, terrorism risk management, or credit-rating of companies. In half of the 20 applications, elicitation is used or proposed for building the BBN structure or for providing probabilities, and again in roughly half of them for both purposes. In the remaining applications, probabilities for BBN are mostly derived from data. This shows that elicitation has become an important contributor to BBN, but is not needed in all cases.

In their book on expert elicitation, O'Hagan et al. (2006, pp.193-214) devote a chapter to summarizing and listing elicitation case studies, but only cite a few examples referring to the elicitation of inputs for Bayesian Belief Networks, namely McKendrick et al. (2000), Renooij & Witteman (1999), Stiber et al. (1999), and Van der Gaag et al. (2002).

Van der Gaag et al. (1999) describe their approach for eliciting experts' probabilities for an influence diagram in the domain of cancer treatment, which needs a total of nearly 3000 probabilities to be fully specified. They report that they have experienced substantial difficulty in using established methods of probability elicitation, e.g., a numerical scale, the frequency method and lotteries, for eliciting large numbers of probabilities in useful time. This is little surprising, given that techniques for the elicitation of well-calibrated probabilities developed in the field of decision analysis can take up to 30 minutes per number elicited (Druzdzel & Van der Gaag 2000, p.482). Renooij & Witteman (1999) therefore develop a probability scale which combines verbal and numerical assessments, intended to simplify the elicitation of BBN probabilities. Van der Gaag et al. (1999) describe an elicitation method they have developed and applied, presenting the conditional probabilities experts are asked to specify as fragments of text, and making use of the scale described in Renooij & Witteman (1999), which combines numerical and verbal anchors. With this instrument, their two experts were able to provide probabilities at a rate of 150 to 200 per hour. Van der Gaag et al. (2002) refer to the same application as the above papers, but elaborate on the evaluation of the method, the elicited probabilities, and the BBN outcomes.

McKendrick et al. (2000) have built a BBN for supporting the diagnosis of tropical bovine diseases. They have elicited response matrices from 44 experts, in which the experts have stated what percentage of cattle they had seen with a given disease had exhibited a list of symptoms. From this information, point estimates were calculated for the probability of a symptom being observed, given an animal has a certain disease, and these estimates were used to quantify the BBN.

Stiber et al. (1999) have elicited 94 probabilities for a BBN on the chemical process of reductive dechlorination at trichlorethene-polluted sites from 22 experts. Interviews were conducted via phone calls while the experts had a copy of the elicitation protocol at hand, and took about an hour. Experts were asked to specify root node probabilities as well as conditional probabilities, such that each expert specified an individual BBN. The different BBN are used to compare the assessments of different experts, and to deduce consensus on what types of evidence are most and least important. An average model was derived by averaging the probabilities given by the different experts. In Stiber et al. (2004), the same authors develop a more elaborate method for aggregating the different networks, which weighs each expert's BBN according to its consistency with the evidence observed at a given site, calculated by Bayes' Rule.

Despite a careful literature study, I could find no BBN application which deals with the subjective assessment of future events, and therefore with presently unknowable probabilities, as is the case with the BBN I have developed in the framework of this thesis. McKendrick et al. (2000) even point out that they "structured the questionnaire to encourage respondents to deliver their subjective beliefs from a frequentist point-of-view to minimise subjectivity in the responses". They explain that they did so in accordance with a request by Kadane & Wolfson (1998) that only observable variables should be elicited. With due respect to the authors, this 'frequentist perspective of subjectivity' limits the area of application of Bayesian analysis to cases of epistemic uncertainty (for a definition and dicussion, see Section 2.1) and deprives it of the possibility to extend analysis to the intriguing and – from the decision-making point of view – important cases where 'irreducible' uncertainty aggravates a decision. Actually, this perspective eliminates much of the value of Bayesian analysis for the social sciences, where the complexity of individual human behavior and interactions allows no forecasting along the lines of well-established patterns or proven laws, making many variables of interest unobservable in the frequentist sense.

Our research group BRS has decided to extend the Bayesian approach to unknowable quantities of interest. We hold that within the Bayesian approach, truly subjective assessments (i.e., assessments that incorporate not only frequencies of past observations, but also, e.g., intuitions, expert judgements, and experience beyond countable instances) are an important source of intelligence, as long as they are diligently collected and processed, and the use made of them is transparently documented. As argued earlier, when certain knowledge is unavailable, humans tend to base due decisions on their subjective assessments, and it is therefore warranted to provide as much expertise as possible and to make decision processes as transparent as possible, no matter whether important facts can not be or have not been observed. That is why, in Chapter 4, I present a BBN dealing with questions that can not be answered today, containing experts' assessments on currently unobservable variables, which is likely to be a first of its kind.

While the above discussion pertains to the concept of Bayesianism and its admissible applications, there are also more technical aspects in which the present BBN differs from most or all BBN I have come across. Firstly, variables can take discrete or continuous values, and their probabilities can be elicited in different ways. In the case of my BBN, variables are of continuous type and are discretized into different categories in order to facilitate their elicitation and processing. Despite an intensive literature search, I found no case where BBN probability distributions were elicited for continuous variables discretized in a non-dichotomous fashion. For example, the elicitation described in Stiber et al. (1999) relates to continuous variables, but these are discretized in a binary way ($P(x > a)$ is elicited). Other elicitors have asked experts to give the probabilities of dichotomous events (e.g., does a symptom occur or not) from a set of probability categories (e.g., McKendrick et al. 2000), or on a continuous scale (e.g., Van der Gaag et al. 1999). I found that eliciting probabilities for intervals in the variable space was sufficient for the purposes of my BBN. This reduced the burden of elicitation compared to the difficulties incurred for fitting a continuous distribution (for an example of the elicitation of a continuous distribution, see Section 2.5.5). Reducing the number of possible variable states to a small number of categories also greatly diminished the number of probabilities to ask for, compared to the point estimates used in many BBN.

Secondly, it was hard to find examples where a BBN is fully specified by each expert, individually. In most cases, experts either quantify a BBN as a group (e.g., Van der Gaag et al. 1999), i.e., behavioral aggregation is used, or the assessments of different experts are mathematically aggregated within one BBN (e.g., McKendrick et al. 2000).[15] I only found one case where single experts specified complete individual BBN, and these were compared (Stiber et al. 1999).

[15]Methods of and difficulties with the aggregation of expert judgement are dealt with in Section 2.5.4.

In summary, compared to the difficulties many authors find with eliciting probabilities for BBN, in the case of my BBN, elicitation of probabilities from the experts turned out to be feasible. This may well have been due to the fact that I constructed the BBN with the constraint of not letting CPT grow prohibitively large. In fact, I had the trade-off between exactness and feasibility in the back of my mind when working on the graphical structure, and I have pragmatically made a number of compromises when choosing variables and their dependencies, so as to avoid conflicts both with feasibility of elicitation, as well as with computability of the BBN. Experiences with the elicitation of probabilities for the car CO_2 emission BBN will be discussed in detail in Section 4.4.

Chapter 3

Expert Interviews on Car CO_2 Emission Reduction Options

This chapter presents the results from a first series of expert interviews carried out in the framework of this thesis. From July through November 2007, I have interviewed 15 German automotive experts, including representatives from car manufacturers, investors, non-governmental organizations (NGO), associations, science, and media. The motivation was to take stock of the options for the German automotive industry to reduce GHG emissions from passenger vehicles, and to find in how far different experts' assessments of these options conflict or coincide. It is not evident whether OEM are willing to engage strongly to reduce CO_2 emissions from the passenger cars they produce, nor whether consumers are ready to buy less emitting cars if this implies either higher prices or reduced comfort. Even if OEM are willing or are forced to reduce emissions, it is unclear by what strategies they can successfully do so, and what technologies will be helpful. The present interviews served the purpose of bringing some light into these issues. They focused on technologies for emission reductions, possible breakthroughs, costs, prerequisites, and experts' probability assessments for technologies to be widely adopted. While longer time frames and a global scale of analysis may be of interest in regard to the global problem of GHG emission reductions, the main foci have been Germany and the time frame up to roughly 2020. However, questions aiming at whether interview partners could imagine a technological breakthrough in the direction of much lower car emissions were included, and were not linked to a specific timeframe. Moreover, while the emphasis was on technological options for emission reductions within the car sector, questions were open enough for experts to discuss social processes or shifts in modes of individual mobility. Statements on these aspects are included in the present chapter.

The issue of GHG emission reductions is debated intensively and to some degree emotionally. There is a large bandwidth of opinions on what the automotive sector can and should do – on the one hand, there are environmentalists demanding immediate drastic action, and on the other hand, there are actors who think that measures in the reach of the German automotive industry are too small to make any difference, or that climate concerns are exaggerated. The intention of the interview series was to cover the whole spectrum of attitudes and to contrast positions as antithetic as possible.

The present chapter starts with two preliminary sections which describe the interview style and process (Section 3.1) and discuss why experts agreed to the general aim of reducing fuel consumption, a fact that contributed considerably to the success of the interviews (Section 3.2). The description of interview outcomes is composed of four main sections. Section 3.3 presents experts' assessments of options for reducing vehicle fuel consumption. For different, mainly technological but also behavioral options, CO_2 emission reduction potentials, introduction times, market chances, and costs are discussed. As many experts commented on problems in regard to the measurement of emissions, a summary of these concerns is included. Section 3.4 summarizes prerequisites needed for emission reduction options to be successfully implemented. The section is divided into general prerequisites, including a discussion of reasonable regulations, and conditions that have been specified to be essential for specific technologies. In the subsequent Section 3.5, probability assessments for different technologies to be adopted are discussed. These judgements usually relate to chances for the years up to roughly 2020, but some technologies have been considered within a longer time frame. Section 3.6 deals with an outlook on possible developments over a longer time span. Experts' statements on possible breakthroughs and their images of mobility in Germany in 2050 are presented in that section. Finally, in Section 3.7, a summary of the interview outcomes is given, along with conclusions from them.

3.1 Interview Style and Process

The method used were open, guided interviews, conducted in a narrative style. Basically, I followed an interview guideline which can be found in the appendix (see A.1), but the interview style was very contained. Experts were interrupted as little as possible, and digressions from the questionnaire very willingly accepted. For example, two experts started out with presentations they had prepared. The assumption behind this procedure was that experts have an assessment of what are the important facts or stories in the subject area, and the less they are directed, the more they will reveal what is important in their view. However, this procedure entailed that it was not always possible to go through all of the questionnaire. Interviews have been recorded, fully transcribed and partly paraphrased. Paraphrased passages have been sorted according to their content, compared among the different experts, and then summarized. Data collection and analysis has been carried out in a circular process in the style of grounded theory. For a description of the methods used for the interviews and their evaluation see Section 2.5.1. Anonymity of experts has been guaranteed. In this chapter, statements have been grouped in regard to subjects discussed, and can not be traced back to specific experts.

To contrast opinions and identify important vertices, I started out interviewing two actors whom I expected to be polar in their views – an automobile expert from an ecologically oriented NGO and an automotive journalist valuing the manufacturing of premium cars as a competitive advantage for Germany, and doubting the global effect of German automotive CO_2 emission reduction endeavors. When asked about GHG emission reduction options in the German car sector, however, both interview partners came up with remarkably similar assessments. Short-term proposals of both of them focussed on incremental increases in efficiency as well as downsizing cars or motors, while major technical breakthroughs were proposed by none of them.

In a second round, I asked another five interview partners, including two car engineers (one representing an ecologically oriented OEM, and one from an automotive supplier company), and two automotive analysts (one from a think-tank and one from banking) as well as a representative of an environmentally oriented lobby association.

In a third round of interviews, I collected statements from eight more interview partners. These were experts from three OEM, as well as one from a supplier company. Moreover, two researchers from institutes developing car technology were asked, as well as two representatives of lobby associations.

All in all, while the picture continued differentiating with an increasing number of experts questioned, it can not be said that assessments differed systematically from experts focusing on environmental aspects to those focussing on premium car technology or German OEM market chances. Measures proposed and discussed by experts did not vary more among these lines than they varied among experts in general. While more environmentally oriented experts may have judged emission reduction potentials more positively, there was no irreconcilable gap between assessments.

3.2 Why Reducing Vehicle Fuel Consumption?

My intention in conducting expert interviews was to find out how CO_2 emissions from cars could be reduced. As expected, experts did not necessarily think that reducing GHG emissions was a sensible aim for passenger vehicle development. However, it turned out that, for different reasons, experts shared the common aim of reducing fuel consumption. As CO_2 emissions from combustion engines are linearly linked to fossil fuel consumption, reducing vehicle fuel consumption is equivalent to reducing CO_2 emissions from car use. The following arguments led experts to advocate fuel consumption savings.

Eight experts saw endeavors of fuel consumption reduction as related to the aim of decreasing GHG emissions from cars. They made the following statements:

- The current focus is to reduce CO_2 emissions from cars in order to avoid anthropogenic climate change. (5)[1]
- Fuel consumption saving activities are due to the expectation that there will be regulations because of the current climate debate. (2)
- Possible continuing global warming would be a driver for fuel consumption reduction in vehicles. (1)

Four more experts focussed on cost or resource scarcity aspects. They stressed that avoiding CO_2 emissions from cars was either generally not important, or that – due to temporary or absolute scarcity – rising fuel costs were about to eclipse the climate change problem:

- Reducing fuel consumption is important because of the (fuel) cost burden to drivers; the current debate on CO_2 is less important. (1)
- Fuel scarcity may become a main problem: Within the 2–3 years to come, refinery capacities may not suffice to meet growing fuel demand from China and India. (1)
- In a few years' time, energy scarcity will be much bigger a problem than CO_2 emissions (peak oil). (1)
- Traffic fuel consumption needs to be reduced because of responsibility for limited resources. The percentage of traffic in total global CO_2 emissions is negligible. (1)

[1] The numbers in brackets indicate how many experts expressed roughly the given opinion. For reasons of readability, no direct translation of the wording used by single experts is given, but items summarize experts' statements. This notation will be used for listings throughout this chapter.

Finally, three more experts mentioned both aspects, saying that

- CO_2 or climate change as well as energy availability, demand and prices are important reasons for reducing vehicle fuel consumption. (3)

The coincidence of different arguments for the common goal of reducing fuel consumption showed up at an early stage in the interview series. It was a main reason for the fact that statements from interview partners holding divergent positions could be condensed into a rather unanimous acceptance of fuel consumption reduction in vehicles. While ecologically oriented interview partners demanded improvements in fuel efficiency for the sake of emission reductions, consumer oriented views aimed at avoiding high costs for driving, and an automotive sport oriented perspective was to advocate improvements in efficiency as a basis for improving cars' dynamic driving properties. As the general aim of fuel consumption reduction was undisputed, differences mainly arose in the assessments of how and to what extent they could be achieved.

3.3 Measures for Vehicle GHG Emission Reduction

In this section, options for reducing vehicle fuel consumption are described as given by the experts. A first subsection describes a number of small measures for improving fuel efficiency which can be applied individually or in combinations. Then, lightweight cars will be discussed, followed by three subsections on (partly) electric propulsion, namely hybrid, plug-in hybrid, and battery electric vehicles. Two more subsections are dedicated to hydrogen and related propulsion systems, and to different kinds of alternative fuels. An additional subsection deals with social rather than technical measures. Finally, experts' statements in regard to the problems of measuring vehicle CO_2 emissions are summarized.

3.3.1 Efficiency Improvements

When asked about emission reduction options for the 15 years to come (roughly up to 2020), many experts started with improvements of the currently dominant technologies, i.e., cars based on conventional internal combustion engines and drivetrains. All 15 experts mentioned at least some such options, referring to them as efficiency improvements, incremental technologies, or downsizing options. The latter expression is somewhat misleading, as an encompassing bundle of technologies sometimes is referenced under the label of downsizing, which in a narrower sense can be taken to mean measures for scaling down motors only, which is just a part of the package. A second source of fuzziness in the notion of efficiency improvements stems from the fact that many experts include start-stop automatics, and some also the recovery of braking energy into the package, which can also be addressed as features of micro hybrids. For the time being, this fuzziness will have to be lived with. As far as single hybrid features were discussed, they are presented in this section. Hybrid Electric Vehicles, which use combinations of those features, are subject of a separate section (see Section 3.3.3).

3.3.1.1 Measures

The following list includes all options that have been mentioned by at least one expert as a measure that can be applied to conventional gasoline and/or diesel combustion engine vehicles. The numbers in brackets indicate how many experts mentioned the respective technology.

- Start-stop automatics (11)
- Vehicle weight reduction (9)
- Improving aerodynamics (lower C_w-values) (8)
- Downsizing: using smaller motors (less capacity, less cylinders) (8)
- Improvements in turbo charging technology (e.g., multi-stage turbo charging) (7)
- Direct injection (esp. for gasoline engines, e.g., Solenoid or Piezo direct injection; higher injection pressure for diesel engines) (7)
- Optimization or electrification of ancilliary units (e.g., electric steering gear, electric cooling water pump) (7)
- Optimizing the control gear / transmission (e.g., greater number of gears, higher gear rations, or dual-clutch gearboxes) (7)
- Homogeneous charge compression ignition (6)
- Low rolling resistance tires (6)
- Recovery of energy (when braking or driving downhill) (5)
- Variable valve trains (4)
- Recovery of heat energy (from cooling water or exhaust emissions, e.g., through a thermoelectric generator) (3)

- Cylinder deactivation (2)
- Reducing friction (e.g., of wheel bearings) (2)
- Engine-stop when idling (1)
- Gear shift indicator (1)

Most of these measures are either well understood, or are being tested and will be ready to go into production at latest within about the next two car generations. Experts agreed that at least some of theses measures are likely to be taken by car manufacturers in the coming years, while some experts said this would depend on suitable regulation, e.g., GHG emission limits or CO_2-based vehicle taxes.

3.3.1.2 Emission Reduction Potentials

Experts gave their assessments of possible CO_2 emission reductions in different ways: For single efficiency improving measures, combinations of different measures, or as an overall assessment of what could be reduced by a sum of individually unspecified measures. These assessments will be presented in the following.

Some of the measures listed above make rather small contributions to the reduction of fuel consumption in the order of magnitude of some percentage points. Five experts quantified such small-scale efficiency gains in terms of percentage of fuel consumption or in absolute fuel consumption decrease. Table 3.1 summarizes these estimates.

Larger reductions in fuel consumption can be expected from systematic improvements in engines and the combustion process. Ten experts discussed motoric measures, and seven of them gave figures for the emission reduction potential of single measures or combinations:

First, the role of efficient diesel motors was an important aspect. Eight experts mentioned explicitly that diesel technology would play an important role in reducing fuel consumption. They were convinced that today's diesel engines are already highly efficient, and further improvements were yet to come. Two experts compared diesel engines directly to hybrid electric vehicles, stating that today's gasoline hybrids were only slightly more fuel efficient than today's diesels, and that consistent further development of efficiency in diesel motors might, in sum, achieve more than a focus on hybrids. One expert said that within the next two vehicle generations (8–10 years), there was a potential of achieving a 20% fuel consumption reduction of diesel engine cars when including motor downsizing.

Table 3.1: Small-Scale Efficiency Gains

Measure	Estimated Fuel Savings
Start-Stop Automatics	5–8%[1], 3–5%, 4%, 3–4%, diesel: 3.5% and gasoline: 2.5%[1], 0.3 l/100km[1]
Regenerative Braking (and Deceleration)	3–4%, 0.1–0.2 l/100km[1]
Electric Braking Gear	3–5%
Electric Cooling Water Pump	2%
Electric Steering	0.1–0.2 l/100km[1]
Recovery of Heat Energy from Cooling Water or Exhaust	0.08–0.16 l/100km[2], 6–7% of primary energy content
Reducing Weight by 100 kg	4.9%, 0.32 l/100km[2], 0.2 l/100km[1]
Gear Shift or Fuel Consumption Indicator	5–10%, 0.5–0.6 l/100km[1]
Optimizing the Gearbox	7%
Wider Transmission Ratio	0.2–0.3 l/km[1]
Using Low Rolling Resistance or Narrow Tires	2–9%, 0.3 l/100km[1]
Increasing Tire Pressure by 10% or 0.2 bar	2–4%
Reducing Rolling Resistance	3.4%
Reducing Friction Losses	3%
Using Low Viscosity Lubricants	2–5%, 0.1–0.3 l/100km[1]
Storage of Cooling Water Heat	0.1–0.2 l/100km[1]

[1] These savings were explicitly mentioned to apply within the New European Driving Cycle (NEDC). For details on the NEDC, see Section 3.3.10.
[2] These figures were given in gCO_2/km by the experts and transformed to l/100km for reasons of comparability. As it was not clear whether the original figures refer to gasoline or diesel, an approximate correspondence of $1l \hat{=} 2.5\ kgCO_2$ was used.

A second important contribution comes from homogeneous charge compression ignition (HCCI), quantified by two experts. HCCI is a combustion technology combining properties of traditional combustion in gasoline engines (spark ignition) and diesel engines (compression ignition). Fuel and air are mixed homogeneously and then compressed until the mixture ignites spontaneously at multiple points. One expert said that a homogenized combustion process could lower fuel consumption of both diesel and otto engines by some percentage points. However, it would still take years before this technology was ready to go into series production. With synthetic fuels, e.g., biomass-to-liquid (BtL) or gas-to-liquid (GtL)[2], an optimized combustion process could reduce fuel consumption by roughly 10% altogether compared to today's engines. A second expert was more optimistic. He held that optimized HCCI would be applied to a significant extent in the 5–10 years to come. This technology would reduce fuel consumption by 15–20% in comparison to today's gasoline engines.

Thirdly, direct injection, turbo charging and downsizing alone or in combination with further combustion engine technologies were described as measures that could reduce fuel consumption and CO_2 emissions substantially. Five experts gave the following quantified assessments:

A first expert said that direct injection alone could save roughly 17% (Solenoid direct injection) or even 20% of fuel (Piezo direct injection) in gasoline motors, compared with today's port injection systems. Direct injection for diesel motors would save about 25% when compared with conventional port injection. These direct injection technologies already existed in series production. The expert expected the share of gasoline direct injection cars worldwide to grow from currently a few percent to around 30% by 2030. The prospects for diesel direct injection propulsion were an increase from a current share of about 20% to 30%, globally, in 2030.

A second expert pointed out that emission reductions in the same range could be achieved through downsizing and turbo-charging motors. These measures would result in a motor delivering equal (or greater) power as the original motor with reduced fuel consumption. The expert gave an example of a conventional suction engine replaced by an existing smaller, strongly turbo-charged gasoline motor, reducing fuel consumption by 19%.

A third expert attributed a savings potential of 15% to gasoline engines through direct injection, variable valve control, downsizing and turbo charging. In diesel engines, savings of about 8% could be realized through higher injection pressure and variable valve control.

A fourth expert pointed out that there was a CO_2 emission reduction potential in the range of 20% in motor development through turbo charging, downsizing, reducing friction, and changes in ancilliary units. However, it might be difficult and costly to realize these savings.

A fifth expert said that measures such as reducing friction, using variable valve trains, multi-stage turbo charging and downsizing would allow savings in

[2]See the section on alternative fuels (3.3.7) for an explanation of BtL and GtL.

the order of magnitude of 5–10%.

Most experts consented to treat technologies increasing the efficiency of cars as a group. Some experts gave overall estimates of CO_2 emission reductions when combining different measures from this group. Some of them specified what combination of measures would be needed to achieve these savings, while others did not. Below, nine experts' estimates are given, from smaller to greater expected reductions.

The lowest expert estimates for fuel consumption reduction through combined efficiency improvements were in the range of 5–20% (given by one expert), 10–20% (given by two experts, independently) or 15–20% (one expert) by about 2012.

Another expert said that, without engine improvements, 8% of CO_2 emission reduction could be achieved by optimizing the gear box, reducing weight and driving resistance, introducing start-stop systems, and optimizing ancilliary units for both gasoline and diesel propulsion systems. Overall improvements when including motoric measures were roughly 23% for gasoline and 16% for diesel passenger cars.

The next expert proposed that roughly 20% of savings could be realized through a combination of measures including a wider transmission ratio, a gear shift indicator, some weight reduction, improvement of aerodynamic properties (C_w-value), and latent heat storage.

In the opinion of another expert, a 20–25% CO_2 emission reduction was possible through incremental technologies within the 10 years to come. However, he said that it was impossible for some German OEM to reach a manufacturer specific fleet average of 130 gCO_2/km by 2015 because of a high and increasing demand for big cars.

One more expert held the contradicting view that with efficiency improvements, reaching emissions of 120 or 130 gCO_2/km by 2012 was generally possible.

Another expert said that it was possible to reduce fuel consumption by 30% in the 10–15 years to come (by around 2020).

Finally, another expert pointed out that with existing technologies, including a downsized, turbo-charged motor in exchange for a suction engine, a higher gear ratio, a gear shift indicator, some weight reduction, some improvement of the C_w-value, and latent heat storage, a nearly 40% reduction in fuel consumption could be reached. The expert said there was still potential for significant further reduction through incremental measures.

Wrapping up, single smaller measures as described in Table 3.1 mostly have an emission reduction potential of some percent, with the range being roughly from 2 to below 10%. Engine measures, especially improvements in direct injection, downsizing and turbo charging, but also HCCI, can bring about emission reductions of up to 20%. In sum, quantified emission reduction estimates for bundles of efficiency improvements range from 10–20% to more than 40%.

3.3.1.3 Costs

Most experts were reluctant to give estimates for the costs associated with incremental technologies. Numerically explicit statements span a range from 500 €$_{2007}$ for a package of measures saving 20% in fuel consumption up to 2000 €$_{2007}$ for downsizing a diesel motor or for start-stop automatics alone. The latter was contradicted by an expert who said that a start-stop system would currently cost 300–400 €$_{2007}$. One expert gave some examples of technology already available on the market: The BMW 116i emits 139 gCO_2/km, which is 40 g/km less than its predecessor, and costs 500 €$_{2007}$ in excess. Fuel savings have been realized through start-stop, gear shift indicator, electric steering, and changes in ancilliary units. A second example given is the VW Passat Blue motion which emits 15 gCO_2/km less than the preceeding model and costs an extra 275 €$_{2007}$. However, the expert could not say whether these mark-ups were a realistic representation of extra production costs for the new technology.

For vehicle owners, the costs of car technology as calculated over the vehicle lifetime can be an important criterion. In this perspective, costs of efficiency improvements may be partly offset by savings through lowered fuel consumption. One expert pointed out that technologies such as start-stop automatics, efficiency improvements, and some weight reduction had a positive overall payoff, if consumers were ready to pay a surcharge up-front and get payback over time.

Overall, few experts were ready to make explicit statements on costs, and the statements made do not allow a consistent conclusion to be derived. Further inquiry of this issue would be of interest.

3.3.2 Lightweight Cars

More drastic CO_2 emission reductions could be reached by replacing conventional cars with lightweight, smaller, more weakly motorized, and less air resistant cars. This option has been discussed by six out of the fifteen experts.

Three of them judged this option favorably in regard to reductions in fuel consumption. One expert proposed building small, more efficient car bodies with very low weight (less than a ton) and low air resistance, and running them with relatively small diesel motors. If this was done consistently, average fuel consumption of the German automobile fleet could be lowered to about 2–3 l/100 km with existing techniques. He said that this was improbable to happen, but that he expected three-liter cars to be available on the German market with a very high probability, and one-liter cars with a medium to high probability within three years from now.

Two more experts linked the lightweight option to a speed limit. One stated that when limiting the maximum speed of cars to about 160 km/h, motors could be downsized considerably and engine power as well as vehicle weight could be reduced. These measures could raise fuel economy by a third on top of incremental technologies, thus, combined with incremental technology changes, roughly cutting fuel consumption to half. The second one said that for reducing car emissions beyond 120 gCO_2/km, (motor) technical options would be very expensive. Cars then had to become smaller and lighter. He linked this development to a change in mobility culture and to a speed limit. He argued that today's cars were construed for high speed, and that their configuration had to change fundamentally for achieving much lower CO_2 emissions.

Three experts strongly doubted the market chances of lightweight cars on short notice. One said that the saleability of lightweight cars would require a new, less high-speed oriented traffic culture. A second expert said that lightweight construction posed strong security risks. Moreover, he pointed out that lightweight materials such as aluminium or carbon fiber were too expensive for mass production. A third expert agreed that it was technically possible to build cars consuming one to three liters of fuel per 100km. In the past, however, three-liter cars had not been accepted by customers, probably due to their higher prices. Future acceptance of less fuel consuming cars would depend on consumer behavior – to what extent they accepted additional price charges for low-consumption vehicles, or whether they were ready to accept a loss of comfort as constituted by the one-liter car, for example.

Apart from the argument of marketability, one expert doubted that lightweight construction of cars was a step in the right direction for technical reasons. He questioned the appropriateness of carbon fiber, because this material could endanger pedestrians in case of an accident. In his view, a possibly more successful option was steel lightweight construction of car bodyshells, which could reduce their weight by nearly a quarter. He said that this kind of construction would need completely new plants, and thus was more likely to be applied in countries like China or India, where production infrastructure had yet to be built.

In regard to costs for lightweight vehicles, one expert pointed out that massive reductions in vehicle weight and resistance might well lower production costs of cars, and another one said that building such cars would be possible without additional research and development (R&D) efforts.

3.3.3 Hybrid Electric Vehicles

Hybrid electric vehicles (HEV), i.e., vehicles which have a full-fledged combustion engine that is supported by an electric motor, is a subject that was brought up by all experts interviewed. Basically, there are three kinds of hybrids, which differentiate in regard to the functions the electric motor can fulfill.

So-called micro hybrids are driven by a conventional internal combustion engine (ICE). There is an electric motor/generator which can charge the battery through regenerative braking and/or deceleration, manage a start-stop system, and provide auxiliary power. Mild hybrids can have the features of micro hybrids, and in addition, their electric motor can supply torque on top of what the ICE provides. However, purely electric traction is not possible. This feature is only supported by full hybrids, which can also have all previously mentioned features. Again, there are two kinds of full hybrids: Parallel hybrids can drive using only propulsion from their ICE, in purely electric mode, or using power from both sources. Series hybrids have electric traction only. Their ICE is used to generate electric energy and recharge the battery.

In this section, expert statements on HEV are summarized. All energy consumed by HEV is provided by fuels. A subsequent section deals with plug-in hybrids (PHEV, see Section 3.3.4), where the battery can be charged not only via the on-board ICE, but also from external sources, so that PHEV can run on fuels as well as on grid electricity.

3.3.3.1 Emission Reduction Potentials

Experts' judgement on the reductions in CO_2 emissions that may be brought about by hybrid technology varied strongly.

One expert said that micro hybrids, which he defined as using a start-stop system and recuperating braking energy to a very small extent, can save 5–7% of fuel consumption[3].

Two experts gave estimates for mild hybrids, saying that they would save about 15%, or that they could save 31% of fuel consumption in a medium-class gasoline car, respectively. However, savings were limited to driving within cities.

Estimates for full hybrid fuel savings given by the experts were even more widespread, from 10 to 45%, with assessments rather evenly distributed over

[3]Quantifications of single (micro) hybrid features such as start-stop automatics or regenerative braking have been included in Table 3.1.

this range. Sorting views from more sceptic to more optimistic, the following statements were made by individual experts:[4]

- Hybrid technology is economic when used in cities only. Battery manufacturing is an additional problem usually not taken into account.

- Hybridization comes in as a part of an overall catalogue of motoric measures that will be added at some point in the optimization process. Hybrids save about another 10% of fuel on top of savings realized through the homogenization of the combustion process.

- Hybrid cars yield a 20% emission reduction when driven in towns, and less otherwise.

- Fuel consumption reduction of hybrid technology is 15–25% when driving in towns.

- Full hybrids are an important option and reduce CO_2 emissions by 20–25% within the New European Driving Cycle (NEDC)[5].

- In the NEDC, gasoline hybrids can realize fuel savings of 25% as compared to the original non-hybrid motor, while allowing for more dynamical driving properties. Diesel hybrids can realize savings in the same range, but departing from more efficient diesel direct injection motors.

- Current hybrids already save up to 30% of fuel.

- Within the NEDC, hybrids can realize fuel economies of 30% in gasoline engines and of 40% in diesel engines, both compared to today's conventional gasoline engine.

- A full hybrid medium-sized gasoline vehicle saves 41% as compared to a non-hybrid of the same kind.

- Savings from hybrid technology are 40–45% in the NEDC in comparison to a conventional engine of 2005. But savings are much smaller when driving overland, and there are no savings when driving on highways. The hybrid savings rate is reduced with further efficiency improvements of motors.

[4]This list contains all expert statements that related to full hybrids or simply to 'hybrids'. It is not always evident whether experts meant to refer to full HEV, so conclusions have to be taken with care.

[5]See Section 3.3.10 for details on the NEDC.

3.3.3.2 Introduction Chances, Timing, and Market Shares

Many assessments of hybrid technology came with statements on when and to what extent hybrid technology could be adopted.[6] Interviewees expressed that they expected the following tendencies:

Two experts stressed that especially micro or mild hybrids would spread in the short term. One of them expected micro hybrids soon to become widely used, and mild hybrids to become more widely used, as well. The second one regarded hybridization as an useful element of the strategy of most OEM, but doubted the usefulness of full hybrids, both because of their costs and the fact that fuel savings only occur when driving in urban areas.

A third expert was more optimistic in regard to full hybrids. He said that elements of hybridization – from start-stop systems to full hybrids – would play an important role in an overall CO_2-reduction strategy, but could not serve as a general solution. There would be more and more hybrids in series production, especially due to demand on the US market.

A fourth expert expressed the opinion that hybridization would continue. Due to its high costs, full hybrid technology would be applied mainly to large cars, while small cars would only be equipped with devices for recuperating braking energy.

A fifth expert differentiated among fuel types. He stated that gasoline-hybrids would exist on a small scale, and that large cars would be mainly diesel hybrids in the future.

The most optimistic expert was convinced that hybrid technology, including plug-in hybrid development, was the solution to fuel economy and that in the future, each car would be a hybrid.

Some experts gave figures in regard to market introduction time and market shares. Individual experts made the following statements:

- The first generation of not-so-elaborate German hybrids will appear on the market by 2010.
- There will be hybrids on the street by 2015, but the number is yet unclear.
- It will take approximately 10–15 years until a series hybrid driven by a free piston linear generator goes into series production.
- Hybrids will be succesful only for limited markets. The registration share in Germany will be about 5–7% by 2020.

[6] For a discussion of probabilities that different technologies will become established, see Section 3.5.

- Hybrids will stay a niche market in Europe, with less than 10% of sales in 2020.

- Hybrid technology is among the concepts which will be available and massively exploitable in regard to fuel savings in the 20 years to come. The worldwide share of hybrids will be about 5% by 2030.

3.3.3.3 Costs

Seven experts talked about the costs of hybrid technology. Those who gave figures agreed that the excess cost for a full hybrid car was in the range of some thousand €$_{2007}$. One said that today, the extra cost of a full hybrid was 4000–5000 €$_{2007}$, which would diminish with growing production volume. Another expert said that the whole catalogue of motor measures, including homogenization of the combustion process and hybridization, would raise production costs of a passenger vehicle by several thousand €$_{2007}$. A third expert said that hybrid technology would only be applied for special editions in the luxury segment, where customers would be ready to pay some thousand €$_{2007}$ in excess.

Other experts did not give figures. One said that hybrid technology was more expensive than efficiency improvements and concluded that it would be applied mainly to luxury segment cars. He compared the price markup for hybrid technology to the add-on cost for a diesel engine compared to a gasoline engine. Another one pointed out that full hybrids were the most expensive way towards fuel economy, and one said that financially, it was not worthwhile for passenger cars due to high additional costs.
One more expert focussed on the overall expenses of producers, and estimated that it would cost billions and billions for German car manufacturers to produce competitive hybrids.

3.3.4 Plug-In Hybrid Electric Vehicles

Six experts discussed the option of plug-in hybrid electric vehicles (PHEV), which is a step in the direction of battery electric driving. PHEV differentiate from HEV in that their battery can be charged from external sources, which allows them to drive in electric mode for longer distances. The differentiation from battery electric vehicles (which will be discussed in the subsequent section) is not very clear-cut, i.e., PHEV are also sometimes described as (battery) electric vehicles with a range extender. Range extended electric vehicles (REEV) have, e.g., an ICE or a fuel cell on top of the electric motor and battery, but the idea is to predominantly use the battery electric mode, and employ the range extender as a fallback option only.

3.3.4.1 Emission Reduction Potentials

Three experts made explicit statements on the emission reduction potential of PHEV: One of them said that there was the possibility of a 15–30% reduction in fuel consumption, one held that plug-in hybrids would save 40% of the fuel needed, and one proposed that hybrid plug-in technology and electric cars could be an option for reducing GHG emissions by more that 50%, if batteries developed well.

Generally, when barely using the plug-in option, it can be assumed that PHEV generate slightly lower savings than HEV of the same size, due to the larger and heavier battery they are carrying. The net difference in CO_2 emissions when driving on plug-in power depends on the carbon footprint of both the electric energy employed and the fuel replaced, as well as on the efficiency of the two propulsion systems.

3.3.4.2 Timing of Introduction

Four experts made statements on when PHEV will be introduced, ranging from in a few years' time to 2020.
The most optimistic expert said that Toyota would bring the first plug-in hybrids to the market within 2–3 years and go for series production in 4–5 years' time. European car manufacturers, he said, were 5–10 years behind.

Another expert gave a similar time horizon. He said that within 5 years, PHEV might be able to drive a hundred kilometers in electric mode before switching to the range extender.

A third expert said that electric cars with a range extender would appear as series vehicles as of 2015. The range extender could be either a combustion engine or a fuel cell. The first generation of such vehicles would be rather small city vehicles and not as comfortable as today's cars. He added that, as battery development was a limiting factor, PHEV would not be suitable as long-distance vehicles within the next 20 years. In the medium or long run, the electric component of such hybrids would become dominant.

A fourth expert expressed the opinion that plug-in hybrids would only exist as of 2020 or later.

3.3.5 Battery Electric Vehicles

Ten out of fifteen experts discussed whether battery electric vehicles (BEV), which run on a battery recharged from an external source, exclusively, were an option for traffic CO_2 emission reductions. They gave controversial statements on the degree of efficiency. It was generally agreed that BEV did not constitute a short-term solution. Opinions on longer-term perspectives diverged.

3.3.5.1 Efficiency and Emission Reduction Potentials

The emission reduction potential of BEV was hardly discussed. Two experts disagreed both on the efficiency of BEV, and on the expected provenience of electricity for BEV. One of them pointed out that the degree of efficiency of mass-producing electric energy and transferring it to car batteries was low. He said that electric cars were not more efficient than current combustion engine vehicles. He added that the amount of electric energy needed for electric cars would have to come from nuclear energy.

The second expert said that in principle, electric motors would work with a high degree of efficiency. But as currently the energy they would use would be produced from coal, well-to-wheel electric car emissions would be worse than diesel emissions. In general, electric cars operating with solar energy would be thinkable even on a global scale. But it couldn't be said whether and when that option could be employed as solar cells were very expensive and resource-demanding, as well.

3.3.5.2 Time of Introduction and Market Shares

Seven experts gave estimates on when or to what extent they expected BEV to appear on the streets. The following statements were made by individual experts:

- Small electric city vehicles will appear within 5–10 years, especially in megacities and urban centers.
- Small electric cars could start becoming established as city or small distance cars within the 15 years to come.
- In twenty years, electric vehicles may make up for a share of more than 10%, as city and municipal vehicles.
- Within the 20–30 years to come, electric cars will be used as short-distance vehicles within cities, at most. Within this time frame, battery capacities will not allow long-distance electric driving.

- Electric cars are imaginable in the longer term. But they would have to start from a niche, as apparently, large car manufacturers are not ready to produce and offer them.
- Electric vehicles have little market potential because they have to be very light and small, and driving them does not meet current consumer habits.
- Electric driving concepts are currently in the phase of predevelopment.

3.3.5.3 Costs

Two experts made controversial statements about the costs related to BEV. One said that full-size battery-driven electric vehicles were not thinkable at reasonable prices today. Only small electric city vehicles could be realized. A second one said that driving an electric car was a cost-efficient alternative at current electricity prices.

3.3.6 Hydrogen and Related Propulsion Systems

In many of the present interviews, as in the public debate, hydrogen usage in cars was not discussed as the issue of a new fuel only, but linked to technology paths of fuel cell versus ICE. Most experts discussed hydrogen as linked to the fuel cell[7]. This made it difficult to differentiate expert statements on hydrogen from their views on related technologies. This section is a kind of hybrid between the style of the previous sections, which clearly focused on technologies, and the section to come, where alternative fuels will be discussed. I have tried to differentiate the fuel aspect from the technology aspect, and to discuss them separately in the two following subsections.

3.3.6.1 Hydrogen as a Fuel

Hydrogen as an alternative fuel was of interest to twelve out of fifteen experts, none of whom held it to be an option for the shorter term. In regard to time horizon, the following statements were made by different experts:

- Hydrogen has little chances for the 10–15 years to come.
- Hydrogen will be a minimal niche until between 2025 and 2035.

[7] A second topic where a technology and the development of a new fuel interrelate is homogeneous charge compression ignition (HCCI), where the optimized combustion technology may, at some point in time, depend on synthetic fuels with certain qualities (for an explanation of HCCI, see Section 3.3.1). For battery electric vehicles, the supply of electricity to cars may become a problem, but electricity as such is widely available.

- The proportion of hydrogen cars in Germany will be around 2–3% in 2020 and 10% in 2050.
- Hydrogen-driven cars will not play an important role in the 20–30 years to come. They could gain a niche by 2050.
- Hydrogen will exist as an option for the future, along with plug-in and serial hybrid vehicles.

Six experts discussed the provenience of hydrogen. One of them was convinced that it would be generated using nuclear energy, and this option would be exploited in 30–40 years' time. Five experts discussed the regenerative production of hydrogen, three of them being rather sceptic about its success. One said that there were many unsolved problems in the regenerative production of hydrogen, and another one stated that the complexity of the regenerative production of hydrogen made electricity the better option. A third one said that the concept of a hydrogen economy by 2050 had been developed as an idea for storing strongly fluctuating renewable energy. But now, it was becoming thinkable to organize a renewable energy system without relying on hydrogen.

Two different experts judged regenerative hydrogen more favorably, saying that hydrogen might become important if it could be produced from renewable energy sources, and that large-scale emission reduction was linked to the production of hydrogen from regenerative sources.

Other issues discussed in regard to hydrogen include (where the number in brackets is the number of experts who addressed the respective aspect):

- Infrastructure (3), especially the absence of hydrogen filling stations. Two experts saw this as a major drawback, while a third one saw the establishment of infrastructure as a prerequisite in the promising overall perspective of a hydrogen economy.
- Production (3), which was seen as inefficient or too energy-consuming by two experts, and as a current great problem that might be overcome in the future by a third expert.
- Storage (3), which was seen as a general problem for efficiency by one expert, as a drawback that might be overcome in case of a fundamental technological breakthrough by a second one, and as a current but possibly solvable problem by a third.
- Efficiency (2), where one expert said that hydrogen was a fuel with a low degree of efficiency, and another one said that using hydrogen in cars was

uneconomical due to the mentioned infrastructure problems and the fact that hydrogen has to be put under high pressure which costs energy and requires stable tanks, adding weight to vehicles.

- Security aspects (2), given by one expert as a prohibitive point, while a second one said that security checks would be required if hydrogen was used.

3.3.6.2 Hydrogen Fuel Cell or Combustion Engine?

Eleven experts made statements on whether hydrogen would be used with fuel cells, ICE, or both. While six of them discussed the fuel cell only, four named both concepts and were not ready to say whether the fuel cell or the hydrogen ICE had better chances for a future sucess. One expert mentioned the hydrogen ICE only.

Fuel Cell
The six experts who spoke about the fuel cell did not see it as a short-term solution to the car CO_2 emission problem. For all except one expert, the fuel cell was linked to hydrogen as a fuel. In the order from more pessimistic in regard to the success of the fuel cell to more optimistic, the experts made the following statements:

- The fuel cell can not be expected to work within cars – it is too complex, and hydrogen poses additional problems. (1)
- The fuel cell will never make it to the market, or it will take 50–60 years to develop. At present, it is neither a low-emission technology nor an economical solution. (1)
- Fuel cells could be used as a range extender within hybrid propulsion systems, maybe from around 2015 on. They could be used with fuels other than hydrogen. (1)
- Fuel cell vehicles will be one among a bunch of options for future mobility. (2)
- The fuel cell may be operational by 2020, but great research progress has still to be made to get costs down and improve usability. The development is hard to predict. (1)
- The fuel cell is a possibility for realizing a quantum leap in regard to the degree of efficiency of vehicles. Rather small numbers of fuel cell vehicles

will appear on the streets by 2015, and it will take 20–30 years from today until they establish on the mass market, meaning that every second or third car runs on a fuel cell. (1)

- With the fuel cell, CO_2 emission reductions in the range of 80% by 2050 could be reached. (1)

Fuel Cell versus Hydrogen Combustion Engine

Four experts did not commit themselves to either the fuel cell or the hydrogen ICE. Two experts said that hydrogen-driven cars, whether with a fuel cell or hydrogen combustion engine, would not play an important role in the 20–30 years to come. One of them said that they could gain a niche by 2050, while the other one said that this option might become important if hydrogen could be produced from renewable energy sources.

A third expert expressed the opinion that cars running on hydrogen, no matter whether using a fuel cell or a combustion engine, would go into series production in 30–40 years time.

A fourth expert also mentioned both the fuel cell and the hydrogen combustion engine as possible future propulsion concepts, but said that the development of fuel cells was hard to anticipate.

Hydrogen ICE

Finally, one expert discussed the hydrogen combustion engine only, saying that vehicles using this technology were ready for the market now.

3.3.7 Alternative Fuels

3.3.7.1 Biofuels

Biofuels and their prospects received attention from eleven out of the fifteen experts. Their statements relate to two groups of biofuels, namely so-called first generation biofuels which are already produced today, and second generation biofuels.

First generation biofuels are made from food crops. Two types of first generation biofuels are currently used: Bioethanol, produced by fermenting plant-derived sugars to ethanol, and bioesters, made from vegetable oil and alcohol through a chemical process. Both types are currently blended with conventional fuels – the former with gasoline, the latter with diesel.

Second generation biofuels can be made from principally any plant or part of plant, including non-food feedstock. For example, from plant cellulose, sugar molecules can be freed and fermented to produce ethanol, or plants can be gasified in order to produce synthetic fuel from that gas. The resulting fuel is called biomass-to-liquid (BtL). Currently, options for second generation biofuels are studied and demonstration plants have been built, but there is no large-scale commercial use.

Extent of Biofuel Usage

The following assessments of biofuel potentials were given by seven experts:

- Before 2012, no important quantities of second generation biofuels will be on the markets. (1)
- Biofuel admixture can be augmented to 20% by 2020. (2)
- Up to 30% of European fuel/diesel consumption could be replaced by second generation biofuels. (2)
- Biofuels will be sufficiently available by 2015 to 2020, they are a realistic option for the 20–30 years to come. (1)
- Biofuels will enter the scene globally. Second generation biofuels should be exploited as much as morally and ecologically possible. (1)
- 20% of admixture is the upper limit for biofuel usage in Germany. Even this share can not be reached by using only fallow ground for biofuel production. (1)
- Replacing conventional fuels (completely) by pure biofuels is not viable. (3)

CO_2 Intensity of Biofuels

Apart from the extent of availability and admixture of biofuels, their carbon intensity is decisive for the overall emission reduction effect. Seven experts commented on this aspect.

In regard to first generation biofuels, little CO_2 emission savings were expected. One expert said that first generation biofuels might, well-to-wheel, even cause higher CO_2 emissions than fossil fuels. A second expert confirmed that biofuels were currently energy-intensive in production and did not lower GHG emissions, while a third one expressed the opinion that there was an emission reduction potential of some percentage points. Two more experts referred to current bioethanol production from corn in the USA, saying that it was problematic, or that it would reduce CO_2 emissions by 10–15%, respectively.

In regard to second generation biofuels, assessments were more optimistic. One expert expected second generation biofuels to make a contribution to CO_2

emission reduction, without giving a quantification. A second one said that second generation biofuels could certainly save 50% of emissions as compared to conventional fuels. They could make a contribution, but did not have the potential to become an overall solution. Moreover, it was yet unclear to what extent overall CO_2 emissions could really be lowered through this means, as, e.g., carbon fluxes in soils were little understood. The remaining two experts were more optimistic. One of them said that second generation biofuels might lead to an overall CO_2 emission reduction of 80–90%. Generally, biofuels contributed to breaking the fossil monopoly. The other one thought that second generation biofuel was nearly CO_2-neutral, with a well-to-wheel reduction of 90–100%.

Ecological, Social and Technical Aspects

Although the production of second generation biofuels is still in the test phase, in the interviews, technical aspects stood back as restrictions for using biofuels. Ecological or social concerns were mentioned more often.

Four experts discussed ecological aspects. One of them said that the use of biofuels was questionable because of the depletion of soils, and a second one agreed that this problem posed a limit to biofuel use. A third one said that it was unclear how much plant material could be extracted for second generation biofuel production without problems, but proposed that one third of EU fuel consumption could be replaced by biofuels in an ecologically unobtrusive manner. A fourth expert pointed out that, when using all fallow ground in Germany for biofuel production, the resulting amount of biofuels would not even suffice to reach the biofuel quota of 20% envisioned for 2020.

Social or moral aspects were mentioned by four experts, three of whom had also discussed ecological aspects. Increasing competition for farmland, which could lead to limited food availability and rising prices, was seen as a limit to biofuel production by three of them. One among them said that already a 20% biofuel quota was disputable in this respect. A fourth expert opposed this position, stating that second generation biofuels were not competing with food production.

Technical aspects of biofuels were commented on by three experts. One of them said that using vegetable oils was more sensible than producing alcohols or second generation biofuels, as the degree of efficiency was highest in this employment, and the remainder of the plants could then be used otherwise. He discarded the strategy of second generation biofuels as inefficient, stating that the degree of efficiency when turning biomass into liquid was only 20–50%, and should not be combined with the generally low degree of efficiency of an ICE. In comparison, using biomass for generating electricity in power plants would be more efficient. A second expert said that biofuel usage was limited to admixture, as the use of pure second generation biofuels would require a completely new petrol pump infrastructure. A third one pointed out that biofuels were an option for reducing emissions more quickly than through other technologies. As they, however, would not be available in large quantities in the short term, he proposed gas-to-liquid (GtL) fuel as a transitory technology. He said that GtL was chemically identical to BtL and would be available on a larger scale earlier.

One expert expressed the opinion that the biofuel hype was currently getting out of pace, and criticism was becoming stronger.

3.3.7.2 Gas as a Fuel

Two kinds of gas were discussed as fuels in the interviews, namely compressed natural gas (CNG) and liquefied petroleum gas (LPG). One expert said that CNG-driven cars were available in Germany as series cars, while LGP-cars were mostly retrofitted and had gained some importance recently. Six experts discussed such options, but none of them saw them as an important contribution to reducing CO_2 emissions from traffic. In regard to the market chances of LPG and CNG vehicles, single experts argued as follows:

- Vehicles using CNG and LPG are available, but will clearly stay a niche market.
- Gas engines will play a role in the future in combination with downsizing measures.
- The prospect of gas driven vehicles gaining meaningful market shares by 2020 has a medium probability.
- Natural gas is still little exploited as a fuel and has some potential for the years up to 2020.
- There will be important increases in the number of gas driven vehicles over the next 10–20 years, and their share of registrations in Germany will lie somewhere above 10% in 2020.
- By 2030, CNG and LPG cars will have a worldwide share of roughly 5%.

The reason for a possibly growing share of LPG or CNG cars was hardly related to their CO_2 emission reduction potential, which was assessed to be limited. One expert argued that gas driven cars offered an economically attractive alternative to conventional cars, and were also an interesting option in view of gasoline scarceness due to a lack of refinery capacities and growing demand from China. A second expert argued that, as CNG and LPG were already available, it was sensible to use them for extending the limited availability of fossil fuels.

3.3.7.3 Flexfuel and Combustion with Multiple Fuels

When using fuels that are not broadly available, so-called flexfuel concepts allow for vehicles to run on different fuel types. With such a concept, drivers can use a fuel causing less CO_2 emissions where available, but still have a fallback option that offers them the driving range they are accustomed to. When retrofitting cars with an LPG system, e.g., the original gasoline equipment is usually kept. This option of having cars equipped to deal with more than one type of fuel was addressed by two experts. One of them said that in the future, motors will be more flexible so as to cope with changing fuels, or else biofuels will be processed as to fit conventional combustion motors. The other one pointed out that concepts for gasoline/gas or gasoline/hydrogen flexfuel cars existed and that such cars would be developed if strict emission regulations enforced it. He also pointed out that combustion processes using different fuels (gasoline and diesel or hydrogen and diesel) in the same motor were being developed and said that such combustion processes had the potential to save another 10% of GHG emissions on top of other efficiency improvements.

3.3.8 Combining Different Measures

Few experts were convinced that the application of a single technology would lead to major fuel savings in the shorter term. Instead, four experts proposed combinations of some of the measures sketched in the previous sections, which could sum up to emission reductions in the range from 30–40% to more than 50%. The statements were as follows:

- Combining measures of hybridisation, energy management, homogeneous charge compression ignition and weight reduction, raising the admixture of biofuels from today's 4% to 17%, and including the renewal of the car fleet, a reduction of emissions by 30–40% within the next 20 years is a realistic perspective.

- In a gasoline vehicle, a combination of (Piezo) direct injection, hybridization, and downsizing can reduce fuel consumption in the range of 40–50% compared to current gasoline port injection systems.

- The overall emission reduction potential of efficiency improvements and biofuels together is in the range of at least 50% by around 2020.
- It is possible to build a Golf-sized diesel car emitting 60 gCO_2/km through motoric measures (downsizing and turbo charging), hybrid technology, weight reduction in the range of 150–250 kg, improved aerodynamics, reduced rolling resistance, and recovery of heat energy. This requires some development of lightweight concepts, battery technology as well as hybrid and combustion engine potentials.

The last statement, that Golf-sized cars with CO_2 emissions of 60 g/km could be built, corresponds roughly with the most optimistic statement that was made on the potential of lightweight vehicles (see Section 3.3.2), namely that a fleet average fuel consumption of 2–3 l/100km could be reached with current technologies. These two estimates are the largest quantified emission reductions that have been given in the present series of expert interviews.

3.3.9 Consumers' Behavior and Social Aspects

The CO_2 emission reduction measures described in the previous sections are predominantly of technical nature. Their implementation depends mainly on OEMs' decisions and actions, and, indirectly, on customer preferences. Measures discussed in this section differ in that they can be taken either by single actors, e.g., by car drivers, or depend on societal decisions.

3.3.9.1 Ecodriving and Navigation

Four experts proposed options for saving fuel and reducing CO_2 emissions through economic driving style or navigation. Propositions ranged from an ad-hoc improvement through eco-driving training to future electronic coupling of vehicles.

One expert described eco-driving as a low-cost option for emission reduction and said that he perceived people to be more and more willing to adopt a fuel-efficient driving-style. An eco-training test with about 2500 participants had shown that in 99% of the cases, fuel savings could be realized through eco-driving training. Average savings were in the range of 20%, maximum savings for single drivers around 60%.

A second expert said that through changes in driving behavior in combination with traffic management and driver information, fuel consumption could be lowered by 20–25%. Navigation systems could allow the driver to adapt his driving style to features of the route ahead, e.g., she could be advised not fully to accelerate when a red traffic light or a strong curve lay ahead. This, however, would expand driving times by roughly the same percentage as fuel consumption decreased. Another option would be to decrease distances driven through regional concepts, reducing the need to drive.

A third expert agreed that navigation systems should be used for managing driving styles according to upcoming conditions, e.g., traffic lights. He proposed to exploit such information for an anticipatory management of energy storage in hybrid systems, using up energy when occasions for regeneration lie ahead. He proposed that future navigation systems should not only offer the options 'direct' or 'quickest' route, but should also allow choosing the 'most economic' route.

A fourth expert said that in the future, cars could be coupled electronically, which would make traffic more efficient, reduce air resistance, and smooth traffic flow. This would also increase security.

3.3.9.2 Cars as Status Symbols

Six experts discussed the problem that, beyond being a means of transportation, cars also play a socio-cultural role as status symbols. As currently, there is a positive relation between the social valuation of a car and its size and motor power, and as these aspects are positively correlated with CO_2 emissions per kilometer driven, the conflict between cars' social role and CO_2 emission reduction endeavors is obvious. Experts took the following positions in regard to this issue:

Two experts pointed out that an ecological image or low emissions were not a selling point for cars. Different German OEM had tried to establish models with lower fuel consumption on the market, trying to give them an ecological image, but had failed. Both experts said that when placing a new model with both lower fuel consumption and a more powerful motor, it could be successfully sold. A price markup could be enforced due to the improved driving properties of the new model, and the financial leeway gained could partly be used by OEM for improving fuel efficiency. This relation, however, primarily held for upper segments, not for small cars where price markups were difficult to realize.

A third expert found that the number of cylinders was a car owner's status symbol, especially in the USA. This would hamper current downsizing trends, as cars with a reduced number of cylinders would be hard to sell.

A fourth expert said that for making fuel saving cars attractive, they had to be promoted via non-technical incentives. He gave examples such as offering special parking places or access to otherwise non-traffic areas for hybrid cars, or public image campaigns, e.g., showing Hollywood actors driving electric or hybrid vehicles.

Two more experts pointed out how strongly cars are linked to social status. One said that today's cars were prestigious objects, charged with non-technical functions. A change had to start in the heads of people. If they would cherish low-emission cars, these would be bought and produced. A second one said that for reducing CO_2 emissions below 120 g/km, it would be necessary to uncouple image or status aspects from driving a car. A new mobility culture was needed, with smaller, slower cars and different kinds of locomotion.

3.3.9.3 Speed Limit

A controversial question is whether a speed limit, especially on the German 'Autobahn', would lead to important CO_2 emission reductions. Moreover, its side effects on road traffic security and the German economy are disputed. In the interview series, five out of fifteen experts discussed speed limits.

Two of them judged a highway speed limit positively. One of them proposed to limit speed to around 160 km/h, which would promote a development towards less powerful, less fuel consuming motors within the 10–15 years to come. Combined with an encompassing set of efficiency improvements as described in Section 3.3.1.1, speed-limit induced motor development could lead to CO_2 emission reductions by 50%. A second expert consented that an absolute speed limit would help reducing emissions. In his view, to get CO_2 emissions below 120 g/km, a speed limit would be necessary.

A third expert opposed this view, saying that today's cars were large and heavy not because of the speed they are constructed for, but because of security requirements which would be indispensable even at a lower speed. Consequently, he did not believe that a speed limit would change car construction in an important way.

A fourth expert discussed different kinds of speed limits. He said that 30 km/h zones would massively raise fuel consumption, while a 50 km/h limit with a progressive signaling system would be beneficial. For highways, he held reliable dynamic speed limits to be useful, while an absolute speed limit would be detrimental for the German car industry. While he said that reducing maximum speed would help to reduce fuel consumption, in his opinion, the success of German OEM and the quality of the cars they produced depended on unlimited speed. A speed limit would cause a degradation of the German cars' quality and the industry's success, and should thus be avoided.

Finally, a fifth expert said that a speed limit was not helpful as it would cause only minor fuel savings.

3.3.9.4 Fleet Renewal

One more way of reducing emissions is to replace cars from the current car fleet by new cars. One expert pointed out that even if each car was replaced by a similar, but new model, important emission reductions could be realized. He said that the replacement of older vehicles by new ones was the easiest way to reduce CO_2 emissions, as today's cars would emit, on average, 25% less than those built in 1990.

Another expert linked possible massive emission reductions in a new car fleet to a change in car models. He said that technology was available for reducing fleet consumption to 2–3 l/100km. For this, a model change of OEM was necessary which could, technically, happen within three years, but was currently unlikely to take place.

A third expert hinted towards a possible regulation-induced demand shift. If luxury cars would be taxed more heavily in future, she assumed that there would be a tendency of demand to shift towards smaller vehicles, which would reduce fuel consuption.

3.3.10 Measuring CO_2 Emissions

When thinking about CO_2 emission reductions, it is important to take into account how emissions are measured. The most common test cycle currently used in Europe for specifying emissions is the New European Driving Cycle (NEDC). A representation of that cycle is given in Figure 3.1. Over a specified time interval (1200 seconds, or 20 minutes), a vehicle is accelerated and decelerated according to the speed pattern shown in the figure, and resulting emissions are measured. As can be seen, the NEDC contains four equal cycles with a maximum speed of 50 km/h (the ECE-15 cycle, used to represent urban driving) plus, at the end, one cycle which reaches a maximum speed of 120 km/h (the EUDC, extra-urban driving cycle).

The NEDC is often criticized for not representing emissions of an average driver correctly. In the current interview series, this issue was raised by six experts, who had the following objections:

- The NEDC does not realistically cover the (average) driving behaviour of people. (5)
- It judges CO_2 emissions from hybrid vehicles over-favorably, due to its high fraction of city-driving. (2)
- The NEDC does not allow to take aerodynamics into account because maximum speeds are relatively low. (1)

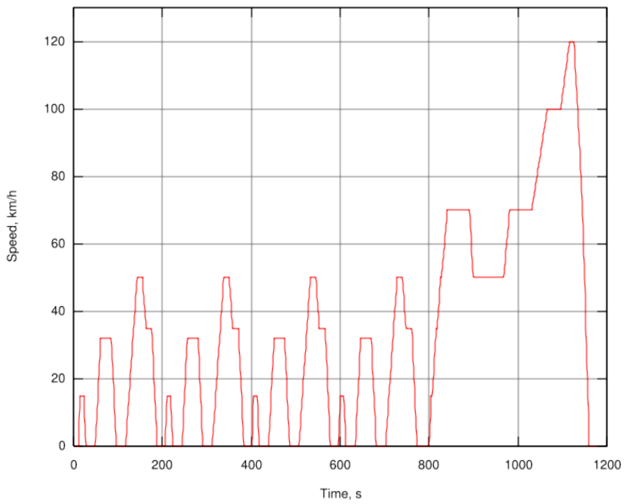


Figure 3.1: Representation of the New European Driving Cycle
Source: Wikipedia, http://en.wikipedia.org/wiki/New_European_Driving_Cycle

Two experts commented on the possibility for OEM to optimize vehicles in regard to the cycle that they know will be applied for measuring CO_2 emissions. One of them said that automobile manufacturers were good at fitting the propulsion systems of cars in such a way that they caused relatively low emissions within the official test cycles. Strong regulations, he argued, would lead manufacturers to configure propulsion systems to fulfill the requirements according to the test cycles, but on the street, these vehicles would not emit any less CO_2.

A second expert explained that for some car models, test results from non-NEDC tests would differ systematically from NEDC results while for others, such differences were negligible. To her, this meant that some models were optimized in regard to NEDC results.

Three experts explicitly demanded the test driving cycle to be changed in a way that it matched real driving patterns more accurately. One expert argued that highway driving conditions should be represented, as well as the use of air conditioning which needed extra energy. Another one proposed that politics should intensively discuss with engineers and design new regulations in a way that the tests they relied on realistically represented the emissions a vehicle causes on the street. He added that under a realistic driving cycle, an appropriate regulation would be to reach average emissions of slightly below

200 gCO_2/km in the coming decade, but nowhere close to 120 gCO_2/km or lower.

3.4 Prerequisites for Measures to be Taken

This section deals with prerequisites which are necessary or useful for fostering car CO_2 emission reductions. First, general conditions named by experts, mostly of regulatory nature, will be discussed. In a second subsection, specific requirements regarding the different technologies discussed in the previous section are described. They concern both regulatory and technical issues.

In 2007, when the interviews were done, it was discussed in the EU that by 2012, passenger car emissions should be limited to 120 gCO_2/km when also taking complementary measures such as biofuel admixture into account, or to 130 gCO_2/km through vehicle technology. For this reason, different experts refer to either 120 or 130 gCO_2/km as the envisaged EU emission limit. For the details of the regulation that has been issued in the meantime, see Section 4.2.5.

3.4.1 General Conditions

While – apart from the rather consentient views on incremental technologies – experts differed strongly in their assessments of viable technological pathways, a point of widely shared understanding regarded prerequisites for reducing German car GHG emissions.

Eleven out of the fifteen experts discussed general social and regulatory prerequisites for fostering CO_2 emission reductions, regardless of by what technology they will be realized. Despite differences in the assessments of what is a reasonable regulation, they agreed that regulation will be necessary to foster meaningful emission reductions.

The following prerequisites were mentioned:

- General regulatory incentives (4), e.g., taxes
- A CO_2-based vehicle tax (4)
- (EU) CO_2 emission targets (3)
- A new company car regulation (1)
- Initial public financial support for new technologies (1)
- A speed limit (1)
- (Changing) consumer preferences (3)

- Pressure from society towards CO_2 emission reductions (2)

Most of these prerequisites concern regulatory issues. The last two points, consumer preferences and social pressure, seem to be different. However, for experts, they were closely related to regulations. The three experts who said that consumer preferences were important also pointed out that regulation will have to play a role if consumers are to prefer cars with lower CO_2 emissions. In contrast, the two experts who demanded pressure from society saw things the other way round, implying that social pressure will be needed to shape regulations in favor of CO_2 emission reduction.

3.4.1.1 Proposed Regulations

Eight experts specified what would be the most reasonable regulations in their view. Five experts made propositions for the much-debated EU regulation. Two of them favored differentiated absolute CO_2 emission limits, where one chose vehicle weight as a basis, and suggested penalty payments for exceedance. A second one said that CO_2 limits for each class of cars would be useful, with cars being classified as, e.g., 'green', 'yellow' and 'red' in regard to their class emission limits. A third expert preferred relative emission reduction targets, e.g., in the range of 25–35% for any OEM, as the fairest solution for an EU regulation. Two more experts favored emission trading systems; one said that a EU-wide fleet emission limit for each manufacturer should be combined with an internal CO_2 emission trading system for the car industry. In contrast, another expert proposed to have a semipermeable emission trading system, where car manufacturers could buy emission certificates from participants of the EU Emission Trading System (EU ETS), but could only sell certificates among car manufacturers. However, this expert expected that an European car emission limit of 130 gCO_2/km on average with penalty payments for exceeding this limit would be realized, instead.

Apart from a CO_2 emission limit, four experts made propositions for other regulations. One said that a change in taxation, such that there is no basic car tax at all, but fuel is taxed very heavily, would make a big difference. Under such conditions, engineers would show that they were able to build much more fuel efficient cars. A second expert pointed out that the basis for taxation should be total costs of ownership, not only the initial price of a vehicle, because putting too much strain on the vehicle price would cause competitive disadvantages for some OEM. Ideally, there should be a global per capita CO_2 budget with tradable permits. A third expert proposed a bunch of measures to help new technologies to become adopted, including incentives through vehicle or fuel taxes, special regulations for urban centers, or driving limits within towns. A fourth expert said to get CO_2 emissions below 120 gCO_2/km, a speed limit would be necessary.

Finally, four experts stressed the importance of regulations to be announced as soon as possible and well in advance, clear-cut, and reliable. One of them added that with a clear-cut, early regulation with sanctioning mechanisms, a European and maybe also a German OEM average of 120 or 130 gCO_2/km could be reached by 2012.

3.4.1.2 Dangers of Regulation

Eight experts pointed out that there was some danger for German OEM if regulations became too strict. Many of these concerns related to the expected EU passenger car emission limit. During the interviews, it turned out that the target figure of 120 gCO_2/km including complementary measures, or 130 gCO_2/km through vehicle measures only, was relatively undisputed among experts. However, the question of what exactly this target should apply to was controversial among experts. Four experts said that, depending on the concrete conditions, the target could cause severe problems. The single statements were as follows:

- An emission limit of 130 gCO_2/km should refer to the European car fleet average. If the limit was valid for every single OEM, it would be difficult for some of them. (2)

- There is a danger of squeezing the automobile industry to such an extent that it can not work profitably any longer. Such an effect has to be avoided. (1)

- 120 gCO_2/km is acceptable as an European car fleet emission limit. However, if this limit has to be reached by all car brands or models, some OEM will have to shut down. Moreover, whether a 120 gCO_2/km average can be reached by 2012 depends on the details of the regulation of complementary measures and on whether the limit refers to new car types only, or to all newly sold cars, as well as on customer choices. (1)

- Drastic CO_2 regulation is a great risk to German OEM. If a strict regulation is enforced, e.g., an 120 gCO_2/km emission limit, German OEM will have to invest heavily into R&D. In order to come up with a decent rate of return under such circumstances, they will consider moving production from Germany to less expensive locations in Eastern Europe. Regulation has to take into account its side effects on company profits, employment, and the economic situation in Germany. (1)

Four more experts discussed different regulatory dangers to the German car industry. One expert said that the biggest danger for German OEM, their 'sword of Damocles', was not a 120 gCO_2/km emission limit, but a deep cut in the existing tax privileges for company cars in Germany. This could evoke massive incentives for consumers to choose smaller, less-emitting cars and would thus endanger OEMs' profits from premium cars.

A second expert generally saw drastic regulation or taxes, as well as worldwide fuel consumption reduction prescriptions, as a threat to mobility and to the existence of (German) OEM. He said that he expected upcoming regulation to change the car sector.

A third one feared that a highway speed limit would threaten the German automotive industry. This aspect has been discussed in Section 3.3.9.3.

Finally, one expert who generally thought that public pressure was useful and should be pinned down in German and EU regulations warned that it should be guaranteed that norms can be fulfilled technically, do not cause excessive costs, and are persistent.

3.4.2 Prerequisites for Specific Technologies to Be Adopted

The above general requirements were seen as important preconditions for the reduction of CO_2 emissions of cars in general. In addition, many experts discussed specific requirements for some technologies. For efficiency improvements, these requirements were mostly of regulatory nature. This reflects that experts estimate these measures to be well understood and developed, but their enforcement to depend on policy. For other technologies, especially those which are linked to the use of batteries or hydrogen, experts also focussed on support or enforcement of development, e.g., through public R&D subsidies. In the following paragraphs, statements on specific prerequisites are summarized.

3.4.2.1 Efficiency Improvements

Six experts pointed out that the introduction of efficiency enhancing measures was related to regulation. They mentioned the following items to be conducive to their diffusion:

- (EU) CO_2 emission limits (4)
- Higher fuel resp. energy prices or taxes (3)
- A (progressive) German CO_2-based vehicle tax (2)
- Consumer habits (2)

- A new German regulation on company cars (1)
- Public perception of climate change (1)
- A prescription of qualities for synthetic fuels (1)

In regard to the prospects of regulation, one expert said that due to the current political and media interest, there was a great chance to get stringent regulations on the EU car CO_2 limit, a suitable German CO_2 based vehicle tax, and a new German regulation on company cars. Another expert agreed that regulation concerning CO_2 emission limits could be expected to be put in place. He also expected similar regulations to appear in other countries, including Japan and California. Then, efficiency improving measures would be taken. A third expert said that he expected significant regulations on fuel consumption to be issued in Europe, China, Japan and the US in the next years. He argued that efficiency improvements were triggered by the expected regulations, but would now probably be realized even if no regulation came, as fuel efficient technology had gained a positive image.

3.4.2.2 Hybrid Electric Vehicles

When asked about the chances of hybrid technology to be adopted, experts said that this depended strongly both on political-regulatory conditions and on technological development, especially in regard to batteries. Seven experts named the following influencing factors for hybrid technology:

- Incentives for customers (3), e.g., special parking lots, hybrid-only zones in city centers, or tax abatements
- Political pressure or regulation for emission reduction (3), e.g., CO_2-emission limits, CO_2 based vehicle taxes, or higher fuel prices (1)
- The ratio of technology costs and savings (1)
- Tax incentives for hybrid R&D (1)
- Battery development (1)
- Further development of electric motors (1)

One expert said he assumed that demand and European regulation would foster the use of full hybrids. Another one expected hybrid technology to be used for large cars, e.g., sports utility vehicles (SUVs), but to spread out to other segments only if regulation supported this.

3.4.2.3 Plug-In Hybrid Electric Vehicles

In comparison to HEV, experts focused more strongly on technological aspects, especially battery development, as prerequisites for PHEV success. The five experts discussing PHEV development named the following requirements:

- (Lithium-ion) battery improvements (3)
- A lot of research in regard to batteries or plug-in hybrids (2)
- Incentives/subsidies for small companies developing and industrializing battery technology (1)
- Common efforts from OEM, universities, and politics for technological development (1)
- Customer demand for renewable energies (1)
- Regulation fostering customer acceptance of cars with a smaller range, e.g., shutting down urban centers for all but electrically driven cars (1)
- Perception of climate change, regulatory framework, energy prices (1)

One expert estimated that the necessary improvement in lithium-ion batteries might come about in the 15 years to come, while another expert thought that it was unclear by when efficient batteries would be available.

3.4.2.4 Battery Electric Vehicles

For BEV, preconditions focussed on battery development, which was explicitly required by all five experts who discussed the issue. One of them held the fuel cell to be the most promising perspective for longer-term massive emission reduction, but said that electric vehicles would become an option if batteries became lighter, cheaper, and resilient to dynamical use. A second expert said that battery technology was also a key component for other future drive concepts apart from BEV, such as further developed hybrid and fuel cell vehicles. A third expert found it questionable whether battery development would be successful and mentioned that current batteries were difficult for consumers to handle.

3.4.2.5 Battery Development

The success of the above described HEV, PHEV and BEV depends on the further development of batteries, as described by many of the experts. Four of them also made statements on what would be helpful for battery development itself to proceed. The following requirements, relating mainly to R&D, were mentioned:

- A lot of research (capacity) (2)
- Public support for battery R&D (2), e.g., tax incentives
- Incentives and support for small companies to accomplish the industrial run-up (1)
- A favorable regulatory framework (1)

3.4.2.6 Hydrogen

For using hydrogen as a fuel, nine experts mentioned that different requirements, such as technical development, supportive regulation, and infrastructural conditions had to be met. While some of them formulated such issues in the sense of prerequisites, others saw them as obstacles which made a success of hydrogen doubtful. The following points were made:

- Hydrogen production and storage has to be improved (3). To this purpose, a lot of research is needed (1), or there has to be a fundamentally new technology (1).
- Much depends on whether hydrogen can be produced from regenerative sources (3). This would make hydrogen an important GHG emission reduction option (2). It currently is an unsolved problem (1).
- With adequate infrastructure, a hydrogen economy would be a promising option (1). Availability of hydrogen at filling stations is an unsolved problem (1).
- In the absence of regulation or fossil fuel scarcity, hydrogen propulsion will develop very slowly (1).
- Great research progress is needed to reduce costs for and improve usability of the fuel cell (1).
- Without a fundamentally new technology, hydrogen remains a fuel with a low degree of efficiency (1).

3.4.2.7 Biofuels

Conditions for biofuels to become established were discussed by four experts. There was a focus on regulation, which was mentioned by all of them, while other aspects were mentioned only once:

- Clear / stable / encouraging regulation (4)
- Subsidies (1)
- Cooperation of the mineral oil industry with OEM (1)
- Research initiatives (1)
- Consumer habits (1)

3.4.2.8 Miscellaneous

One expert said that fuel saving combustion processes, in which two types of fuel are combined, would be applied only if a more demanding CO_2-regulation was put into action.

A second expert said that prospective driving as a fuel saving measure could be supported by more precise navigation data.

A third expert said that a prescription of qualities for synthetic fuels would help OEM to adjust motors in an efficient way.

3.5 Probabilities that Technologies will be Adopted

Experts were asked to give probabilities that certain technologies will become established in the next fifteen years. A five-point scale was used, from 1 referring to 'is very unlikely' to 5, 'is very likely' to become established. Due to time constraints, this question was asked in nine of the fifteen interviews, only. Out of the nine experts asked, six used the five-point scale, two used a different scale, and one refused to give probabilities. In four of the interviews where probabilities were not explicitly asked for, verbal likelihood assessments were given for some technologies.

Thus, results are not complete, and not all statements are directly comparable because of different scales and verbal statements. Nevertheless, these assessments give important insights into experts' expectations in regard to the future development, and will be presented in the following subsections.

Each subsection contains a probability table for a given technology to be widely adopted. In the first column, experts are numbered. They have been numbered identically in each table, such that, e.g., statements from expert 1 in the table concerning efficiency improvements have been given by the same expert as those from expert 1 in the HEV table. In the second column, probability statements from the experts are given on the five-point scale. Numbers in brackets mean that they have not been given directly by the expert, but are translations of either numbers given on a different scale, or of verbal statements. In the third column, statements in brackets are the original statements made by an expert. Non-bracketed text is additional information that is added because it further specifies or confines what exactly the probability assessment refers to.

Table 3.2: Probabilities of Efficiency Improvements to Become Established

Exp.	Prob.	(Original Statement), Additional Information
1	(4)	(Positive vote.) Will come if policy changes the framework stringently.
2	5	For both gasoline and diesel vehicles.
3	(4–5)	(9–10 out of 10), if there is an ambitious EU emission limit, fuel tax, and higher fuel prices.
4	5	
5	(5)	(Motor-downsizing will take place.)
6	5; 3–4	5 for the 3-liter car; 3–4 for the 1-liter-car to be adopted.
7	(5)	(This will come.)
9	(5)	(6 on a 6-point scale. This will definitely establish.)
14	(5)	(Start-Stop will definitely be adopted on a large scale. Stepwise turbocharging, downsizing, and weight reduction will come.)
15	5	Otto motor and diesel motor optimization as well as further efficiency improvements are very likely to become established.

This table shows the probability assessments of efficiency improvements to be widely adopted which 10 out of the 15 experts have specified. Experts have been numbered identically in every table in this section (i.e., 'expert 1' always refers to the same person). Probabilities are given on a five-point scale from 1 – very unlikely to 5 – very likely to become established. Probabilities in brackets mean that the expert has not directly specified this number, but it has been deduced either from an assessment given on a different scale or from a verbal expression. The table's third column gives the original statements (in brackets), as well as any additional information that is important for interpreting the probability assessments (non-bracketed text).

3.5.1 Efficiency Improvements

Ten experts gave their assessments of the chances of efficiency improving measures to be widely adopted. Four of them used the proposed five-point scale, two used different scales, and the remaining four gave verbal assessments. As Table 3.2 shows, experts judged the prospects of these technologies quite unanimously. Seven of them said that efficiency improving measures were very likely to be taken. This includes verbal statements that they 'will' or 'will definitely' prevail, which were interpreted as 'very likely' (probability level 5). Of the remaining three experts, the assessment of one was translated to a probability of 4–5, another one to 4, and the third one subdivided his judgement, saying that 3-liter cars had probability 5 while 1-liter cars were less probable at 3–4.

A bit of care has to be taken in interpreting results because most experts treated efficiency improvements as a bundle which, however, contained different measures for different experts. For example, two experts stressed that efficiency improving measures would be applied both to otto and diesel engines, while it is unclear how other experts judged this issue. Some specified what techniques they expected to prevail, e.g., motor-downsizing or start-stop, while others did not. The additional information given in the table is intended to convey as exactly as possible what single experts referred to. The fuzzy character of 'efficiency improvements' has been mentioned earlier, and can not be resolved here. Although assessments of different experts are not necessarily directly comparable, grouping them together still allows to deduce that most experts agree that some of these measures will be taken, albeit possibly different ones.

3.5.2 Hybrid Electric Vehicles

In comparison to the probability judgements expressed in the previous section, expectations on HEV success are more diversified, as can be seen from Table 3.3. The assessments of eleven experts spread over the neutral and positive probability levels of 3–5. As can be seen from the additional information, judgements are, again, not completely comparable. Experts refer to different hybrid stages, from micro to full hybrids. Moreover, one expert relates his statement explicitly to a longer time frame than the 15 years proposed by the interviewer, and two differentiate among car segments. All in all, experts seem less convinced of a success of HEV in the nearer future than of the introduction of efficiency improving measures.

Table 3.3: Probabilities of HEV to Become Established

Exp.	Prob.	(Original Statement), Additional Information
1	4	Not necessarily full hybrids.
2	3	
3	(4–5)	(9–10 out of 10), if there is an ambitious EU emission limit, fuel tax, and higher fuel prices.
4	3–4	
6	(4)	(Gasoline hybrids will play a certain role.)
7	4–5	Within the 20–25 years to come.
9	(5)	(It is coming, also full hybrids, for the US market.)
11	(5)	(It will come, but only for some top car models.)
12	(5)	Hybrids will come. Micro hybrids will diffuse very broadly in the near future. Mild hybrids will establish broadly, as well.
13	(3)	(I am not sure whether full hybrids will establish.)
15	4	Probable. For a limited segment, surely.

This table shows the probability assessments of HEV to be widely adopted which 11 out of the 15 experts have specified. Probabilities are given on a five-point scale from 1 – very unlikely to 5 – very likely to become established. Probabilities in brackets mean that the expert has not directly specified this number, but it has been deduced either from an assessment given on a different scale or from a verbal expression. The table's third column gives the original statements (in brackets), as well as any additional information that is important for interpreting the probability assessments (non-bracketed text).

3.5.3 Hydrogen Propulsion

For hydrogen, probabilities given have to be treated extremely carefully. First, only one of the five assessments has been given as a number on the 1–5 scale, and all others are translations. Translations into numbers in this case express only tendencies, as statements were made in a rather open or conditional way. Second, different subjects are involved, as two of the statement concern the fuel cell, and three the probability of hydrogen as a fuel to become established. Third, three experts, namely those who held the establishment of hydrogen or the fuel cell to be probable or very probable, explicitly alluded not to the 15-year perspective, but to 20 up to roughly 40 years from now (see additional information in Table 3.4).

The five assessments are rather evenly distributed over the whole range of

Table 3.4: Probabilities of Hydrogen-driven Vehicles to Become Established

Exp.	Prob.	(Original Statement), Additional Information
4	1	Relates to the Fuel Cell.
5	(5)	(I am very sure that hydrogen produced from nuclear energy will be used in 30–40 years.)
6	(1–2)	(Hydrogen as a fuel will not be adopted if there is no completely new technology.)
10	(4–5)	(We need the fuel cell. But it will take 20–30 years until the fuel cell will be established on the mass market.)
15	(3–4)	(Hydrogen could be the fuel of the future, in the perspective of 2050.)

This table shows the probability assessments of hydrogen-driven vehicles to be widely adopted which 5 out of the 15 experts have specified. Probabilities are given on a five-point scale from 1 – very unlikely to 5 – very likely to become established. Probabilities in brackets mean that the expert has not directly specified this number, but it has been deduced either from an assessment given on a different scale or from a verbal expression. The table's third column gives the original statements (in brackets), as well as any additional information that is important for interpreting the probability assessments (non-bracketed text).

1–5. The diversity of judgements of hydrogen and fuel cell chances may stem from the differences in time frame, as experts considering a longer time frame saw hydrogen chances more positively. It can be concluded that none of the experts expected hydrogen propulsion to play an important role until 2020.

3.5.4 Battery Electric Vehicles

As can be seen from Table 3.5, assessments of BEV probabilities again span the whole range from 1–2 to 5. Only four experts have made statements, none of which coincide. As with hydrogen, one statement explicitly refers to a time frame which is longer than 15 years. Two experts are rather sceptic, one is sure that the electric car will become an alternative, and the fourth assessment lies in between.

3.5.5 Biofuels

Only two experts gave their estimates of probabilities that biofuels will be widely adopted. Both said that biofuels are very likely (or sure) to become established in the 15 years to come. Of all items discussed, this is the most

Table 3.5: Probabilities of BEV to Become Established

Exp.	Prob.	(Original Statement), Additional Information
4	2	
6	(5)	(The electric car will come, as an alternative.)
14	(3–4)	(I can imagine that the path of plug-in electric cars with range extender will be chosen.)
15	(1–2)	(If at all, electric vehicles will occupy a niche as small city vehicles within the 20–30 years to come.)

This table shows the probability assessments of BEV to be widely adopted which 4 out of the 15 experts have specified. Probabilities are given on a five-point scale from 1 – very unlikely to 5 – very likely to become established. Probabilities in brackets mean that the expert has not directly specified this number, but it has been deduced either from an assessment given on a different scale or from a verbal expression. The table's third column gives the original statements (in brackets).

Table 3.6: Probabilities of Biofuels to Become Established

Exp.	Prob.	(Original Statement), Additional Information
4	5	
12	(5)	(Biofuels will establish worldwide.)

This table shows the probability assessments of biofuels to be widely adopted which 2 out of the 15 experts have specified. Probabilities are given on a five-point scale from 1 – very unlikely to 5 – very likely to become established. Probabilities in brackets mean that the expert has not directly specified this number, but it has been deduced either from an assessment given on a different scale or from a verbal expression. The table's third column gives the original statements (in brackets).

uniform assessment, which comes as no surprise as it also has the lowest number of assessors.

3.6 Outlook

During most of the interview, a time frame of 15 years, roughly up to 2020 was addressed. However, the development of some technologies or social changes with a massive impact on CO_2 emissions from traffic is likely to take longer. In order to capture experts' assessments of such changes, they were asked whether they could imagine any breakthroughs, regardless of the time frame, and what they thought mobility in Germany would be like in 2050. In two subsections, this section describes experts' answers to these two questions. Moreover, some experts alluded to the global dimension of the problem of climatic change and discussed possible emission reductions from passenger vehicles in Germany in this regard. Such statements are summarized in a third subsection.

3.6.1 Breakthroughs

The interviews included the question whether an expert could think of technical breakthroughs in the sense of massive GHG emission reductions. The idea was to make sure that experts would not only focus on technologies that were currently developed, but would also sketch further options they might have in the back of their minds. As can be seen from the following statements, the majority of experts could not imagine a major breakthrough:

- A technical breakthrough in the automobile sector can not be expected. (9)
- There will not be one technology, but a combination of measures or subsequent steps towards lower CO_2 emissions. (4)
- Massive GHG emission reductions are possible if a new traffic culture can be established including speed limits, smaller, lighter and slower cars, but also less traffic, more shared or public means of transport, as well as bicycles and walking. (2)
- With plug-in hybrid cars, massive emission reductions can be reached. (1)
- Electric driving must be considered, but depends on the development of the battery and on the provenience of electricity. (1)
- A breakthrough in battery technology is thinkable. (1)
- Hydrogen, of course. (1)
- Large emission reductions are possible only with hydrogen. (1)
- A technological breakthrough in second generation biofuels would be a great advance. But the expert couldn't say when such a breakthrough could be realized, and whether costs would be bearable. (1)
- Pyrolysis oils (i.e, oils produced through decomposition of any organic material by heating under pressure, in the absence of oxygen) could be an interesting option. (1)
- Well-to-wheel, there is nothing more efficient than the diesel engine. (1)

3.6.2 Mobility in Germany in 2050

The question on breakthroughs in the automotive sector, discussed in the previous subsection, was not explicitly linked to a specific time frame. The intention behind that question was to find out what might be promising technological development paths from today on. As a final question, experts were then asked to give their expectations on what mobility in Germany might look like in 2050. Answers to this question are often related to possible breakthroughs experts can imagine, because their occurrence would reshape mobility options for the decades to come. But the question was more encompassing in its scope, rather addressing experts' imagination than asking for a realistic forecast. Answers contain expectations as well as hopes of experts which partly relate to technology, but also to possible future mobility development in a wider sense, including changes in lifestyle.

Ten experts came up with statements on their expectations or hopes in regard to technologies. They said that, by 2050:

- Telematic solutions, e.g., electronic coupling of individual vehicles, car-to-car communications, and intelligent traffic systems will be available. This will enhance security, make traffic much more efficient, or offer relief for drivers in crowded traffic situations. (5)
- There should/will be zero-emission vehicles. (3)
- There will be vehicle concepts or propulsion systems we can not imagine today. (3)
- Cars running on hydrogen will be on the streets (1), go into series production (1), or occupy a niche market (1).
- There will be a mix of different vehicle concepts, including electric cars. (3)
- A largely emission-free all-in-one device suitable for every purpose ("eierlegende Wollmilchsau") will have been found by 2050. Maybe hydrogen produced by nuclear fusion, or something we can not imagine yet. (1)
- Passenger cars will predominantly run on regenerative electric energy (photovoltaics, wind and solar thermal energy). Mineral oil fuels will play a minor role. (1)
- Hopefully, there will be vehicles with very low resistance and CO_2 emissions, where occupants are placed in a line behind each other. (1)

Five experts held the opinion that there might or should be changes in mobility concepts and lifestyles. They said that, by 2050:

- It is possible that ownership of cars will be less important, but people will have the option to use different cars, share cars, or public transport will be more important. (4)
- People will live in villages with their workplace, friends and leisure opportunities nearby, so that riding a bicycle will suffice for guaranteeing mobility. (1)
- For megacities, new traffic concepts could be invented which do not rely on individual vehicles. (1)

While the former statements relate to important changes, either in technology or mobility concepts, three experts were convinced that there will be no radical changes:

- In 2050, mobility in Germany will be similar to today. There will be improvements but no utopian changes. (2)
- In 2050, there will still be a high proportion of cars with combustion engines. (1)

3.6.3 Climate Change as a Global Problem

Although this was not part of the questionnaire, some experts stressed that focussing on GHG emission reductions from the German automotive sector – or even from the transport sector worldwide – would not have an important impact on global greenhouse gas emissions and climate change. As this aspect was important to six experts, their positions are summarized in the following.

One expert pointed to the fact that climate change was a global problem and inferred that current German endeavors to reduce CO_2 emissions from passenger cars would not make any difference, as the overall share of emissions from cars was too low. Moreover, meaningful changes would take extremely long. Due to long product replacement cycles, it would take 10 to 14 years before current efforts would make a perceptable difference. He compared OEM to large tankships, which took a long time to slow down or change direction. A second expert pointed out that traffic made up for 17% of anthropogenic CO_2 emissions, and these, in turn, were only 3.5% of total CO_2 emissions. Thus, traffic would account for less than 1% of overall CO_2 emissions. Reducing CO_2 emissions from traffic could not be expected to save the world, and should not be treated as if, in the current debate.

Three experts discussed the effect of motorization in emerging economies. One said that, as climate change was no exclusively German problem, it would be a great challenge to find a new, non-fossil path of motorization for emerging countries. Others were sceptic in regard to a possible low-carbon mobility development. One expert stressed that low fuel consumption was no selling point on the markets of emerging economies, and their demand for large, heavy cars would make European traffic emission reduction efforts obsolete. Another expert pointed at the large numbers of passenger vehicles Chinese OEM were aiming to sell in the years to come. In regard to global CO_2 emissions, the number of cars was going to be more problematic than each single car's emissions, although, of course, each single car should contribute as little emissions as possible.

In regard to industrialized countries, the same expert found that CO_2 emission reduction regulations were on their way. Although in Japan and the US, people were thinking that the German climate debate was somewhat exaggerated, emission laws would eventually converge to common standards. He appreciated this development, because it meant that the same low-emission vehicles could be sold all over the world, allowing reasonable quantities to be produced. A second expert agreed that strict regulations were envisaged not only for the European Union, but also for other markets. For China, there already were regulations with bans on registration for non-compliant vehicles which had been tightened in 2008. For Japan, there was a law for reducing fuel consumption which would apply from 2010 on. And between 2010 and 2015, US legislation could be expected to come up with a CO_2 regulation at least as strict as the European one.

Finally, two experts said that other sectors might be able to reduce emissions much more efficiently than the automotive sector. One of them pointed out that with the same effort which had been and still was made by automotive OEM, much more could be achieved when working on, e.g., the degree of efficiency of heating systems. A second one agreed that economically, avoiding CO_2 in the automotive sector was inefficient. CO_2 abatement costs were much lower for insulation of buildings, or for solar thermal power used for heating water and buildings.

3.7 Summary of Expert Interview Results

This section summarizes the main findings on CO_2 emission reduction potentials of different technologies, prerequisites for their establishment, and probabilities that they will be adopted, as discussed in detail in Sections 3.3 throughout 3.5.

Conclusions are drawn on the relations between experts' assessment of emission reduction potentials, prerequisites and probabilities. Finally, it is discussed what the present analysis tells us about the prospects of different technologies for the future.

Table 3.7 compiles the ranges of quantified CO_2 emission reduction potentials given for different technologies or measures. Minimum and maximum CO_2 emission reductions refer to the extreme values given, usually by different experts. Where minimum and maximum coincide, only one quantitative estimate was given. Beneath the headline 'No. of experts', the column titled 'Subj.' gives the number of experts who discussed the respective subject, and the column called 'Quant.' refers to the subset of experts who quantified the emission reduction potential of the measure. For HEV, in some cases it was hard to sort out whether expert statements related to full or partial hybrids. In Table 3.7, all statements on HEV not explicitly referring to mild or micro HEV were subsumed under the heading of HEV, which consequently can not be guaranteed to contain full HEV-related statements, only. The 'Subj' column has been left empty for mild and micro HEV, because it was unclear how many experts have discussed these options. For biofuels, the number of eleven experts discussing them includes all experts who said something on either first or second generation biofuels, or both. Under the heading of 'Ecodriving', statements on ecodriving only as well as in combination with navigation are subsumed. Although one expert gave maximum fuel savings of 60%, this figure was not included in the table because it relates to single drivers and is no realistic representation of possible average fuel savings of such a measure when applied to all drivers.

In a way, **efficiency improvements** are the most conventional techniques that can be applied, excerting incremental savings on standard technology. They have been discussed by all 15 experts. Nine of them have quantified their emission reduction assessments, which range from 10–20% to nearly 40%. As prerequisites for efficiency improving measures to be implemented, experts demanded regulation and consumer pressure, exclusively. This reflects the overall opinion that the respective technologies are well understood and ready to be exploited if conditions are suitable. In regard to probabilities that such measures will be taken in the 15 years to come, experts gave a relatively unanimous and positive judgement. On a scale from 1 (very unlikely) to 5 (very likely), ten experts gave assessments which ranged from 3–4 to 5, with a majority of seven experts holding that efficiency improvements are very likely (or sure) to be widely adopted.

Hybrid electric vehicles (HEV) are a second option that was brought up by all experts, with nine of them giving quantitative assessments for emission

Table 3.7: Emission Reduction Ranges for Different Measures

Measure	CO_2 Emission Reduction			No. of Experts	
	Minimum	–	Maximum	Subj.	Quant.
Combined Eff. Meas.	10–20%	–	nearly 40%	15	9
- DI, Downs.& TC[1]	5–10%	–	20%	12	5
- HCCI[2]	some %	–	15–20%	6	2
Leightweight Vehicles	33%	–	2–3 l/100km[3]	6	2
HEV	10%	–	40–45%	15	9
HEV, mild	15%	–	31%		2
HEV, micro	5–7%	–	5–7%		1
PHEV	15–30%	–	>50%	6	3
BEV	no figures given			10	0
H_2	no figures given			12	0
Fuel Cell	80%	–	80%	10	1
Biofuels, 1st gen.	negative	–	10–15%	12	5
Biofuels, 2nd gen.	≥50%	–	90–100%	12	3
Gas	no figures given			6	0
Combined Measures	30–40%	–	60 gCO_2/km[4]	4	4
Ecodriving	20% (av.)	–	20–25%	4	2
Speed Limit	<120 gCO_2/km[4]	–	50%	5	2

The first two columns give minimum and maximum emission reductions of the different options as specified by (usually different) experts. Two further columns give the number of experts who discussed the respective option ('Subj.') and who gave a quantified assessement ('Quant').

[1] Direct Injection, Downsizing & Turbo Charging

[2] Homogeneous Charge Compression Ignition

[3] This figure does not specify an emission reduction, but an absolute fuel consumption level that can be reached.

[4] These figures does not specify emission reductions, but absolute vehicle emission levels which can be reached.

reductions ranging from 10 to 40–45%. Assessments of fuel savings, however, have to be treated carefully, as they apply to driving within cities only. Some experts were sceptic in regard to the diffusion of full HEV technology because of its costs. German OEM were said to lag behind in comparison to competitors in regard to this technology. Concerning prerequisites for HEV implementation, there was a focus on regulatory incentives or pressure, but aspects of technological development or support thereof also entered the picture. Probability assessments for HEV to become established until 2020 ranged from 3 to 5, with opinions relatively homogeneously distributed over this interval, showing that experts' opinions spread from neutral to very likely that HEV will prevail.

Biofuels were discussed by 12 out of 15 experts, and possible emission reductions were quantified by 5 and 3 experts for first and second generation biofuels, respectively. Emission reductions expected from first generation biofuels ranged from negative – meaning that well-to-wheel, CO_2 emissions increase – to 10–15%. Second generation biofuels were assessed more positively, with more than 50% to 90–100% of emission reductions. Many experts adverted that fossil fuels could be replaced by biofuels to a limited extent only, and therefore could not be an overall solution. For the biofuel option to be exploited, prerequisites mentioned were mainly regulatory incentives or pressure, but technological development (support) was also demanded. Probability assessments were given by two experts who agreed that biofuels were very likely (or even sure) to be used until 2020.

Three more options for reducing car emissions by up to more than half were discussed. First, **leightweight vehicles** were mentioned by six experts, and emission reductions were quantified by two of them. The lower estimate was that a third of current CO_2 emissions could be saved, and the higher one was that lightweight cars would allow an average fuel consumption of 2–3 l/100km to be reached, which is less than half of the average consumption of newly registered vehicles in Germany today. One expert assessed it to be very likely that a lightweight three-liter car will become established on the German market and expected one-liter cars to appear within the three years to come with a medium to high probability.

Second, **plug-in hybrid electric vehicles** (PHEV) were discussed by six experts, as well, and emission reductions proposed by three of them were between 15–30% and more than 50%. Regarding prerequisites for PHEV, experts' demand for R&D activity clearly outweighed regulatory issues. A second focus was on customer acceptance.

Third, different **combinations** of efficiency improvements, hybridization and biofuels were proposed and quantified by four experts. The lower boundary of estimates was that a combination of measures would reduce CO_2 emissions by 30–40%. The upper estimate was that it was possible to produce Golf-sized cars emitting 60 gCO_2/km only, which is more than 60% less than the average emission of today's new car fleet in Germany. For this option, little was said on preconditions and probabilities.

Further technologies which could possibly allow massive CO_2 emisson reductions from passenger cars are **battery electric vehicles** (BEV) as well as **hydrogen** and the **fuel cell**. These were discussed by 10–12 experts, each, but nearly no quantitative assessments of emission reduction were given. Moreover, in the opinion of experts, the time frame where these options could achieve important reductions extends far beyond 2020.

Although no numerical assessment was made, for BEV, the expected range of CO_2 emission effects was extremely large: One expert said that currently, well-to-wheel BEV emissions would be worse compared to diesel, because they were driven using coal-based electric energy. Two experts could imagine future BEV to be driven by solar or nuclear energy, which could result in zero-emission driving. While hydrogen as a fuel was seen critically by some experts, others expected it to be produced regeneratively or using nuclear energy, so that it could become a zero-emission fuel. However, no expert saw hydrogen as an option for the next few years. Similarly, the fuel cell was seen as a possible option for massive CO_2 emission reductions of up to 80%, but this related to 2050. For the nearer future, expectations were modest. Regarding prerequisites for BEV and hydrogen cars to become established, demands focussed on R&D rather than on regulatory issues. Hydrogen propulsion was also said to depend on suitable infrastructure. For both BEV and hydrogen propulsion, expectations varied strongly among experts. The whole range of probabilities that these technologies will be adopted, from 'very unlikely' to 'very likely', was present, with no two experts coming up with the same assessment.

Finally, non-technical measures, i.e., **ecodriving** and **speed limits**, were discussed by 4 and 5 experts, respectively. Quantified emission reductions for ecodriving, including improvements in navigation, were in the range of 20–25%. This option can be seen as the cheapest and quickest way of reducing CO_2 emissions per km driven, as it depends uniquely on single drivers' choices. Single experts said that a speed limit was needed for evoking emission reductions to below 120 gCO_2/km. Maximum emission reductions were given as 50%. However, in this perspective, the speed limit was seen as a necessary condition for triggering an overall development towards less emitting cars, not as a sufficient condition. There were experts who expected less or unimportant effects of a speed limit, but they did not quantify them.

In the previous paragraphs, experts' assessments of emission reductions achievable through different technologies have been summarized, alongside with prerequisites for and probabilities of technologies to be adopted in the nearer future. In this summary, it has been shown that there is some correlation between

- the number of experts willing to give quantitative emission reduction estimates and the spread of their estimates,

- the experts' assessment of the state of development of the same technology, as derived from the prerequisites which experts deem necessary for establishing the technology, and
- the number of experts willing to give a (high) probability that the technology will be adopted, and the spread of such assessments among the experts.

From efficiency improvements via HEV and PHEV to BEV and hydrogen propulsion, required prerequisites shift gradually from regulatory to technological aspects. The interview series has shown that most experts (11 out of 15) agree that suitable regulation is an indispensable prerequisite to fuel consumption reductions from cars. Especially the EU emission limit received attention. Apart from regulation, several experts have mentioned that consumer preferences and social pressure play a vital role. Technical development, however, is not seen as a general prerequisite, but is necessary only in regard to less well developed technologies. Thus, from more to less developed technologies, the focus gradually moves from regulation and societal pressure towards technology development incentives or support.

The technologies where further development was seen as a prerequisite coincide with those where inhomogeneous probability assessments were made. Thus, while expert assessments are rather unanimous in regard to well developed techniques, especially efficiency improving measures, they vary more for HEV and PHEV and most when it comes to techniques that have not reached maturity and the development and success of which remains uncertain, i.e., BEV, fuel cells, or hydrogen propulsion in general.

In summary, it can be said that for different technologies the development and functioning of which is increasingly uncertain, expectations on emission reduction potentials and technology establishment are more and more divergent. Or, the other way round, the better a technology is developed and known, the more expert expectations have converged. This is plausible, as experts form their expectations based on the information and personal experience they have, which may result in greatly differing assessments for new and largely unknown technologies. When a technology develops, more information becomes available and knowledge is shared among actors, which may lead to a convergence of expectations.

Among the experts questioned, expectations have largely converged for efficiency improvements. They agree that the German automobile industry is about to pick the relatively low hanging fruits of efficiency gains in current combustion engine technology through incremental measures. Depending on whether the more optimistic or the more pessimistic assessments turn out to be true, this may or may not suffice for reaching a target of 120 gCO_2/km. However, if fuel consumption and CO_2 emissions from passenger vehicles have to be reduced even more strongly in the future, efficiency improvements alone can not be expected to be the solution.

A second step that, according to the experts, is rather likely to be taken is a hybridization strategy, but it is unclear whether full hybrid technology will be applied for a broad range of passenger vehicles. In addition, biofuels can be expected to play a role for the nearer future.

Beyond these steps, there is no agreement on a concept for massive passenger car CO_2 emission reductions. In fact, options that one expert deems the most effective or the most likely are inefficient or unsalable in the eyes of another expert. As a short-term massive CO_2 emission reduction option, a lightweight vehicle strategy as proposed by some experts seems technically feasible, but is discarded by others. As an alternative, some experts have proposed combining efficiency improvements with hybridization or lightweight technology, but there is no consensus to take this path, neither. In the longer run, some experts are convinced that BEV or hydrogen vehicles will be able to offer a solution for low- or even zero-emission mobility, while others think that these technologies will never experience a breakthrough. On the basis of the present expert interviews, the question which, if any, of these options will be able to deliver massive CO_2 emission reductions in the future can not be answered reliably. In the following chapter, a Bayesian Belief Network will be applied for an in-depth exploration of some of the open questions regarding car technology and CO_2 emission development and their drivers.

Chapter 4

An Expert-based Bayesian Belief Network for Analyzing 2030 German New Car Fleet CO_2 Emissions

This chapter introduces a Bayesian Belief Network (BBN) that builds on the expert interview results presented in the previous chapter. It extends their scope by trying to come up with a quantification of 2030 German new car fleet emissions, in contrast to the focus on single technologies taken so far. Furthermore, the impact of important drivers identified before, i.e., regulation and technological development, is to be further specified and quantified in terms of conditional probabilities. Research questions are as follows:

- How much CO_2 will the 2030 German new car fleet emit on average, and how can emissions be reduced?
- What is the (quantitative) impact of certain alternative regulations?
- What is the (quantitative) impact of selected technological advancements?

The idea of building this BBN was born during a workshop at Carnegie Mellon University's Engineering and Public Policy Department (EPP) at Pittsburgh, USA, where previous results were discussed.[1]

[1] I am very grateful to Prof. Mitchell Small, Carnegie Mellon University (CMU), Pittsburgh, for his proposition to build a BBN and for much further coaching and consulting on the issue. Furthermore, many members of CMU's EPP staff contributed by discussing and criticizing my draft BBN and supported its transformation to its final version.

In contrast to the semi-quantitative interviews described in the previous chapter, the BBN approach is more formalized. It uses a predefined general structure of variables and their interrelation which builds on the previous results. The idea is to combine the general structure with quantified expert assessments of CO_2 emissions conditional on some of the drivers identified in the first interview round. To derive these assessments, a second set of interviews is necessary, where experts frame their expectations in terms of conditional probability distributions over future states of central variables.

This approach is somewhat experimental in several regards. First, BBN are not a common tool in economic analysis. Second, the present BBN is designed to examine questions the answers of which depend to a large extent on the future development of different factors, involving technological development as well as socio-economic factors and human behavior. Answers to such questions are uncertain in the Knightian sense, i.e., they are 'unknowable'. In spite of an intensive study of literature, I could not find a single example where a BBN has been used for analyzing this kind of question, before. Thus, the aim of this study is twofold: Gathering insights into the defined research questions on the subject of car CO_2 emissions, as well as evaluating in how far the method of expert-based BBN can be applied in situations of true uncertainty, e.g., for analyzing dependencies and possibly for giving policy advice. Third, the present BBN also contains some novel elements regarding its technical details. For quantifying the BBN, probabilities are elicited in the form of conditional probability distributions over continuous variables, discretized into a number of categories. Despite an intensive literature search, I have not found other BBN for which probability distributions over continuous variables have been elicited in a none-binarily discretized fashion. Moreover, in the present application, each expert has been asked to completely specify his individual BBN. I could only find one other BBN with this property. For a more detailed discussion of the present approach in comparison to previous studies, see Section 2.5.7.

In this chapter, first, the structure of the BBN will be presented. In subsequent sections, input parameters to the BBN and their scenario variants will be given, as well as equations underlying the deterministic BBN nodes. Then, elicitation methods and results are discussed. Finally, results from running the BBN under different scenarios are presented and evaluted.

4.1 The Structure of the BBN Model

The structure of the complete BBN, also called the graphical model (variables and linkages only), can be seen in Figure 4.1. The BBN was created in a

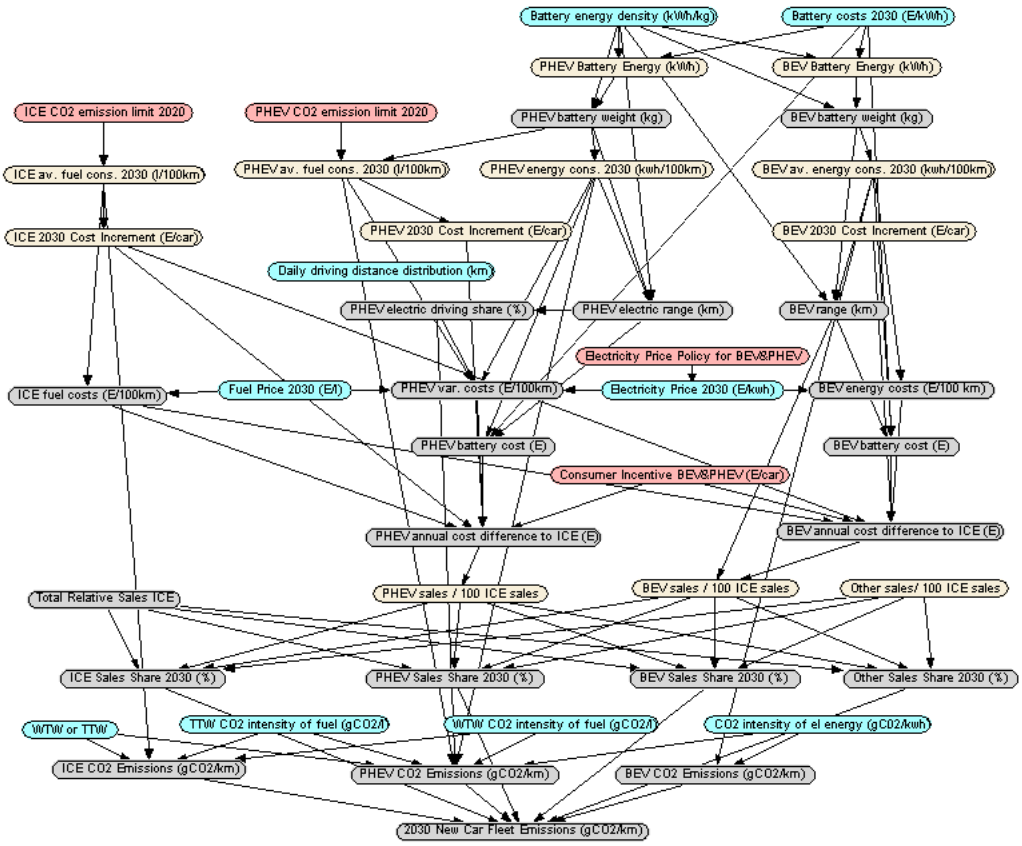


Figure 4.1: Structure of the BBN

modeling process which took more than half a year, from the first few linked nodes to the final structure. It is based on the outcomes from a the first round of interviews described in the previous chapter, and on the advice and remarks of scientists and practitioners I discussed it with. Differing from the first interviews, the time horizon of the BBN was extended by 10 years, focussing on 2030, in order to leave some room for new technologies to establish. The BBN consists of 46 nodes altogether, the colors of which relate to their contents and the way their states are determined within the BBN. There are

- 12 nodes with conditional probability tables (CPT) elicited from experts (beige nodes in Figure 4.1),
- 4 policy scenario nodes (red nodes),
- 9 nodes containing scenario parameters and distributions regarding technological development, prices, and CO_2 intensities of fuels (blue nodes), and

- 21 deterministic nodes which are calculated within the BBN (grey nodes).

Interview results motivated the choice of the following three groups of technologies represented within the BBN:

1. Internal combustion engine vehicles (ICE), which includes all vehicles running on energy from fuels, exclusively. In this definition, ICE include hybrid vehicles from mild to full hybrids, as they do not use any original energy sources except fuel (electric propulsion relies on recuperated energy only).

2. Plug-in hybrid electric vehicles (PHEV), i.e., cars which have both a combustion engine and an electric motor and can consume both fuel and electric energy from the grid, stored in a battery.

3. Battery electric vehicles (BEV), running only on electricity charged into their batteries via plug, using an electric motor.

In the graphical model, the variables relating to the three groups of technologies are roughly placed in three columns with ICE on the left handside, PHEV in the middle, and BEV on the right handside. In Figure 4.2, variables relating to the three technology blocks are marked by three vertical blue-shaded areas.

ICE were chosen because they are today's standard passenger vehicles and techniques for improving their efficiency are under way. PHEV and BEV were added because they are the currently most debated and disputed technologies for possibly extreme CO_2 emission reductions. In the first interview series, their prospects both in regard to emissions and marketability remained unclear, so that it seemed worthwhile to quantify experts' assessments of those technologies. Further vehicles technologies, e.g., hydrogen fuel cell vehicles (HFCV), were not explicitly modeled in the BBN. This was avoided in order to reduce complexity to a manageable extent and seems justified as from the first series of interviews, there were few hints that HFCV were likely to play an important role by 2030. A catch-all variable ('others') was included in the BBN to leave room for experts to consider technologies not explicitly modeled.

Figure 4.2 can help guiding through the BBN. Sets of variables relating to different steps are marked by the five yellow-shades horizontal areas. These five steps are determining battery parameters, fuel and energy consumption for each vehicle type, vehicle overall costs (purchase and variable costs), sales shares of vehicle types, and finally vehicle type and overall fleet CO_2 emissions.[2]

[2]This chronological step-by-step logic is used here because it facilitates the understanding of the BBN structure. Still, BBN allow for both forward and backward induction. Evidence

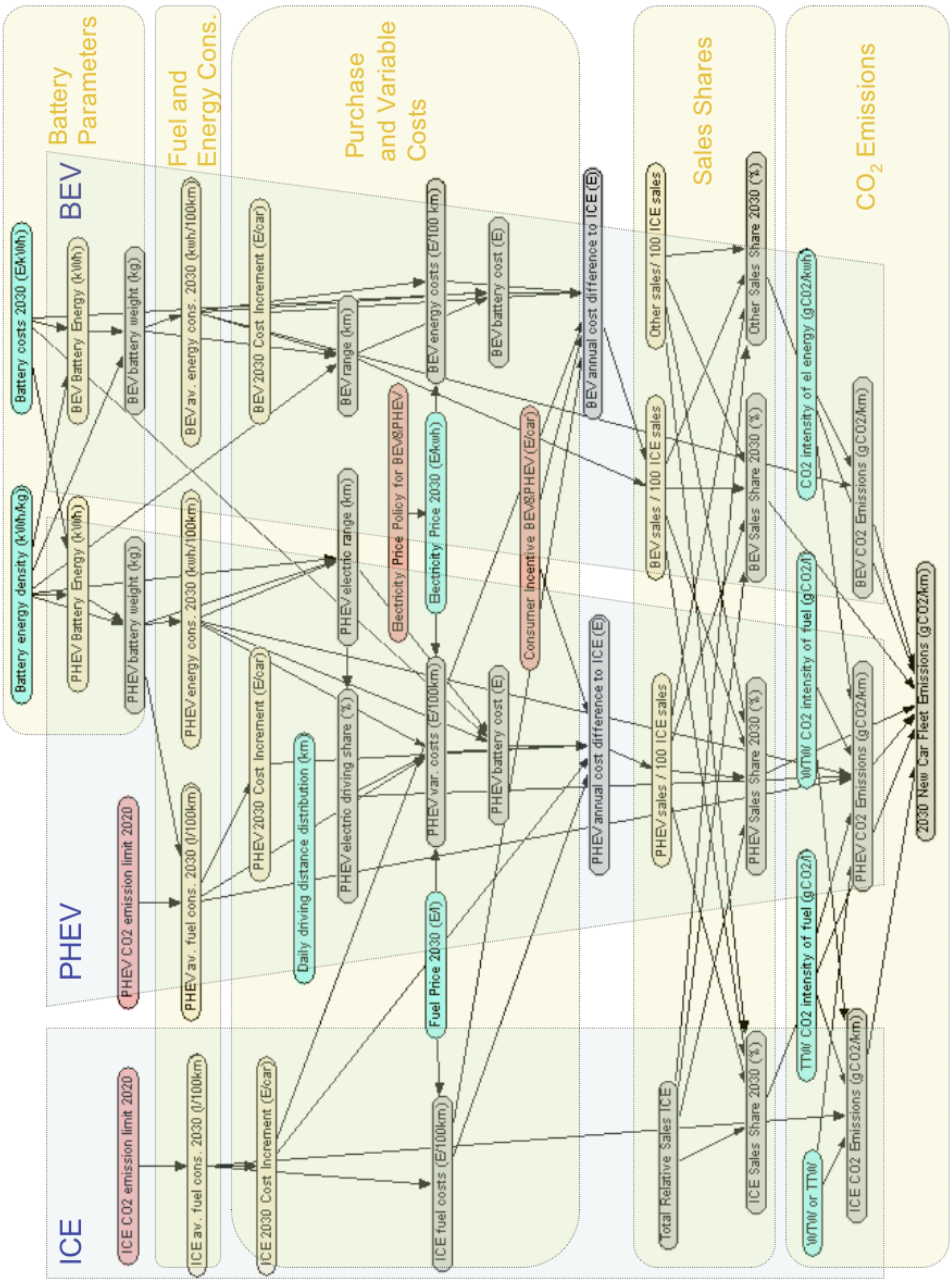


Figure 4.2: Structure of the BBN – Building blocks

For specifying **battery parameters**, conditional probability tables (CPT) for battery energy installed in PHEV and BEV are elicited from experts. Battery energy is modeled as conditional on battery development, representing the finding from the first interview series that technological development is important for BEV (and PHEV) to establish, but uncertain. In the BBN, two scenarios are proposed for battery energy density and battery costs in 2030, respectively (a description of the scenarios will be given in the following section). The values are given to the experts as inputs.

Fuel and energy consumption for the different vehicle types constitute four more variables the CPT of which are determined through expert elicitation (ICE consume only fuel, BEV only electricity from the grid, and PHEV both). Based on a finding from the first series of interviews, regulation is assumed to be important to bring down ICE fuel consumption. Thus, there are regulation nodes, more precisely, nodes offering different states for a 2020 passenger car CO_2 emission limit issued by the European Union, as parents of the ICE and PHEV fuel consumption nodes. For the PHEV and BEV energy consumption CPT, battery weight is assumed to be the only parent node. Battery weight, in turn, is calculated from battery energy and battery energy density determined in the previous step.

CPT for **incremental costs** for each vehicle type as compared to the costs of today's ICE are elicited (for PHEV and BEV, these costs exclude the battery). For ICE and PHEV, these nodes are modeled conditional on 2030 fuel consumption levels reached by the vehicles, representing the finding that reducing fuel consumption was considered costly by most experts in the first interview series. For BEV, cost increment is unconditional. Then, a number of calculative and parameter nodes are introduced which allow to compute annual cost differences for PHEV and BEV compared with ICE. Roughly, what is done here is to evaluate purchase cost differences of the vehicles, to distribute them over the expected useful life, and to add estimated annual variable costs.

The values derived for PHEV and BEV annual cost differences to ICE are then used as inputs for the experts' estimation of their 2030 **sales shares**. For technical reasons, experts are asked to give sales shares for PHEV, BEV, and other vehicles as a percentage of ICE sales in 2030.

The remaining nodes are used to determine **CO_2 emissions**. No more expert inputs are needed in this step. Introducing a number of scenarios for 2030 fuel and electricity CO_2 content, probability distributions for CO_2 emissions can

can be entered at any node, e.g., when entering a value for 2030 German new car fleet CO_2 emissions, the network will find the most likely combination of states of the other nodes given this value.

be computed in calculative nodes. CO_2 intensities are used to first determine the specific CO_2 emissions of each vehicle type, and then vehicle type emissions are weighed by sales shares to deduce 2030 German new car fleet average CO_2 emissions.

A detailed description of BBN inputs will be given in the following sections. In Section 4.2, parameters and scenarios for policies, technical development and prices are discussed, and in Section 4.3, equations for all calculative nodes are given.

Once all inputs to the BBN have been provided – marginal probability tables for all nodes that do not have parents ('orphan' nodes), in the present BBN the red and blue nodes, as well as CPT for the beige nodes – the BBN can be compiled. First, probability tables for the calculative (grey) nodes are filled as prescribed by their equations. Then, compilation is carried out, constructing an inference engine for the BBN and updating the probability tables of all nodes to the current state of information contained in the BBN.[3] The technical details of the compilation process have been presented in Section 2.4.4.

When compiled, the BBN can be displayed in so-called belief-bar style, shown later in this chapter in Figure 4.30. This style has the advantage that the probabilities of each variable being in any of its states can be read off directly. However, with all variables displayed in belief-bar style, the BBN becomes too large to be readable when printed on a standard page. Therefore, a hybrid presentation of belief-bar and labeled-box style has been designed and used for the expert interviews, which can be seen in Figure 4.3.

I am aware of the fact that the choice of nodes and linkages presented in this section is nothing more and nothing less than my personal informed decision. It represents my assessment of what variables and linkages are most important to the subject, given the restrictions of feasibility. Numerous other structures could be thought up (and, in fact, were thought up, modified or rejected during the research process). In order to evaluate how well the BBN does in representing the experts' view, some question regarding the validity of the model were included in the elicitation. This assessment will be dealt with in Section 4.4.4.

[3]Generally, after compilation, the inference engine allows the network to update instantaneously when new information is entered. The present BBN, however, is too large to be processed this way. As a solution to this problem, a sampling update function was added by Netica personnel on request, which has been used for much of the evaluation of the BBN. This function carries out an approximate updating of the BBN and has to be launched manually each time new information is added.

4.2 BBN Parameters and Scenarios

While for a number of nodes in the BBN, experts are asked to specify probability tables, both the number of nodes and the subject area where expert input is used have to be restricted. One constraint is brought about by the fact that expert elicitation demands considerable resources both on the side of the expert (interview time) and the interviewer (preparation, interview time, evaluation and reporting). Furthermore, an expert on car technology does not necessarily have similar expertise on, e.g., the electricity system, or may not be willing to judge future fuel price development. Thus, expert elicitation has been restricted to some core nodes concerning car technologies and their prices, car energy consumption, and sales shares. As the BBN covers a wider range of issues, for other nodes, scenarios have been derived from literature. The basic idea underlying the choice of scenarios is that they should cover a relatively wide range of developments which are possible for the future according to recent studies. Given uncertainty on the future, of course, it can not be assumed that one of the scenarios considered represents the development that will actually take place, and it can not even be guaranteed that the future development is covered by the range of extremes chosen. Scenarios can be seen as best guesses at the author's current state of knowledge, much in the sense of priors which can be updated as time goes by and more information becomes available. One of the advantages of the BBN approach is that new values for scenarios can be entered easily.

4.2.1 Scenarios for CO_2-Intensities

Traffic CO_2 emissions can be derived as the product of the amount of energy consumed and the CO_2 intensity of an unit of energy. While in the present BBN, the first factor enters as expert assessment, the second one is dealt with in the form of scenarios.

To come to a realistic conclusion on how much CO_2 emissions are caused by transport, and to be able to compare them among vehicle types with different propulsion systems, emissions over the whole cycle of energy provision and consumption have to be taken into account.

For example, for conventional fuels such as gasoline or diesel, the bulk of emissions is generated when burning the fuel. However, a part of the emissions results during resource extraction, transport and refining of primary energy.

In contrast to conventional fuels, for biofuels, emissions from burning cause no additional carbon input to the atmosphere, because all carbon released when burning it has previously (relatively recently compared to the production of fossil resources) been absorbed by the plants the fuel is made of. Thus, the standard way of accounting for biofuel emissions is to count only additional emissions caused during biofuel production, e.g., emissions from process energy.

For electric energy, there are no local CO_2 emissions when using it, and all related emissions occur during electricity generation, e.g., during primary energy extraction and transformation in the case of electricity from conventional power plants. Thus, for electric driving, only emissions from the process of providing energy have to be taken into account.

The concept of 'well-to-wheel' (WTW) emissions sums up all emissions over the life cycle of the different types of energy, i.e., 'well-to-tank' (WTT) emissions from fuel and energy production and 'tank-to-wheel' (TTW) emissions from energy use within a vehicle. Therefore, in order to be able to compare emissions related to the use of different fuels and powertrains in a realistic way, this study focusses on WTW emissions. In the following, scenarios for WTW CO_2 intensities of both the 2030 fuel mix and 2030 electricity will be derived.

4.2.1.1 CO_2-Intensity of the 2030 Fuel Mix

The BBN node 'fuel CO_2 intensity' allows to consider different values for the carbon intensity of the German fuel mix in 2030. Fuel mix carbon intensity depends, on the one hand, on the carbon intensity of the different fuels, and on the other hand on their shares in the overall fuel mix. Table 4.1 summarizes current carbon intensities for different fuels in Europe. WTT and TTW carbon figures as well as fuel energy content are taken from a recent study by Bodek & Heywood (2008, p.25). The authors have selected a subset of pathways from a larger set given in Concawe et al. (2007). They have chosen the wheat ethanol, biodiesel and natural gas pathways included in Table 4.1 because they consider them to be the most likely future fuel pathways, and/or to represent median values for their fuel types. The authors also indicate that carbon intensities were likely to change over time, but say that there are no reasonable estimates regarding the nature of such change (Bodek & Heywood 2008, p.24).

I base fuel CO_2 intensity calculations for the BBN on the data shown in Table 4.1, using it as the best available assessment. Although the carbon content of biofuels may change according to the way they are produced, variations of fuel carbon content for a given fuel type over time will not be considered. However, the range of fuel mix CO_2 intensities will be chosen in an encompassing way, such that it leaves some room for covering such changes.

Next, an assessment of possible fuel mixes for the year 2030 is needed. Table 4.2 summarizes different scenarios for such mixtures, based on literature and current European Union (EU) policy. Scenario A describes a case where

Table 4.1: WTT, TTW and WTW[1] Carbon Intensities of Different Fuels

Fuel	WTT (gCO_2/MJ)	TTW (gCO_2/MJ)	WTW (gCO_2/MJ)	Energy (MJ/l)
Petroleum Gasoline	12.5	71	83.5	32.2
Petroleum Diesel	14.2	76	90.2	35.8
Wheat ethanol	59.2	0	59.2	21.2
Rapeseed-oil Methyl Ester Biodiesel	49.15	0	49.15	33
Natural Gas	16	52.8	68.8	37[2]

Source: Bodek & Heywood (2008, p.25), building on Concawe et al. (2007)
[1] WTT – Well-to-tank CO_2 emissions, TTW – Tank-to-wheel CO_2 emissions, WTW – Well-to-wheel CO_2 emissions, i.e., the sum of WTT and TTW emissions.
[2] given in MJ/m^3

fuel mix does not change from today. The diesel share of 37% is calculated as the number of kilometers traveled by Germans in 2008 using diesel passenger vehicles (i.e., 216,630 million km (Kalinowska & Kunert 2009, p.879)), divided by the overall numbers of kilometers driven by Germans in 2008 (i.e., 584,589 million km (Kalinowska & Kunert 2009, p.875)). In scenario A, gasoline is assumed to make up for the remaining 63%.

Scenario B is based on a projection for the share of diesel related to all kilometers driven in Germany in 2030 by IFEU (2005, p.13). The authors expect the proportion of diesel in the fuel mix to increase, assigning a share of 58% in 2030. For simplicity, in this scenario, the share of renewables is treated as negligible, thus the gasoline share is set to 42%.

Scenario C is derived from a scenario called 'diesel dominate' considered in Bodek & Heywood (2008, p.12) for Germany in the year 2035, where an even larger diesel share of 75% is assumed.

The final two scenarios include relatively large shares of renewables. In scenario D, an overall share of 15% is assumed, departing from the EU policy goal of replacing 10% of transport fuels by renewables by 2020 in all EU member states (see European Parliament & Council (2009)), and assuming that their share continues growing in the ten subsequent years. For both the renewable and non-renewable fraction, an equal share of diesel-type and gasoline-type fuel is used. Finally, scenario E describes a strongly renewable pathway, including 10% of ethanol and biodiesel each by 2030. Moreover, it is assumed that the gasoline share is much higher than the diesel share, an assumption which can be used as a boundary for a low-carbon trajectory.[4]

Table 4.2: Scenarios for the 2030 German Fuel Mix (Shares)

Scenario	Gasoline	Diesel	Ethanol	Biodiesel
A, Status quo	0.63	0.37	0	0
B, Diesel Increases	0.42	0.58	0	0
C, Diesel dominates	0.25	0.75	0	0
D, Renables Increase	0.425	0.425	0.075	0.075
E, Strongly Renewable	0.5	0.3	0.1	0.1

Scenarios are based on:
A – Kalinowska & Kunert (2009); B – IFEU (2005); C – Bodek & Heywood (2008)

All in all, these scenarios do not describe the only thinkable futures. Still, they can serve as a proxy for a plausible range of fuel mixes in the year 2030. Table 4.3 displays the carbon intensities of the fuel mixes described in Table 4.2, derived by combining the fuel shares with the fuel carbon intensities given in Table 4.1. Little surprising, the strongly renewable scenario E results in the lowest fuel mix carbon intensity of roughly 2600 gCO_2/l, while the highest emissions of nearly 3100 gCO_2/l result from the diesel-dominated scenario C.

While the renewable scenarios D and E are not based on literature, but rather on assumptions according to current EU and German energy policy, resulting carbon intensities are in the range of those expected by Nitsch (2008). Considering direct (i.e., TTW) CO_2 emissions only, the study proposes a fuel carbon intensity of 2060.8 gCO_2/l_{fuel} for the so-called lead scenario (Nitsch 2008, p.168), which describes a development where Germany reduces its greenhouse gas (GHG) emissions to 20% of the 1990 level by 2050 and reaches intermediate policy goals for GHG emission reduction, increases of energy productivity, and an enhancement of renewable energies by 2020. In that scenario, the share of renewables in the German fuel mix is 15.8% in 2030 (Nitsch 2008, p.167), similar to that in the present scenario D. Further scenarios calculated in that study assume either an even more efficient and climate friendly development

[4]Natural gas is not considered in any of these scenarios. As its carbon content is lower than that of the standard conventional and higher than that of the renewable fuels, similar fuel mix carbon intensities result if it replaces partly conventional and partly renewable fuel in scenarios D and E. Scenarios A-C would be slightly less carbon intensive if a fraction of natural gas was added. Thus, considering natural gas would be unlikely to account for large changes in the overall range of scenarios.

Table 4.3: 2030 Fuel Mix Carbon Intensity for Different Scenarios (gCO_2/l)

Scenario	WTT	TTW	WTW[1]
A, Status quo	441	2447	2888
B, Diesel increases	464	2538	3002
C, Diesel dominates	482	2612	3094
D, Renewables increase	603	2128	2731
E, Strongly renewable	641	1959	2600

This table shows the carbon intensities of the fuel mixes described in Table 4.2, derived by combining the fuel share scenarios with the fuel carbon intensities given in Table 4.1.
[1] WTT – Well-to-tank CO_2 emissions, TTW – Tank-to-wheel CO_2 emissions, WTW – Well-to-wheel CO_2 emissions, i.e., the sum of WTT and TTW emissions, all given in gCO_2/l of the hypothetical 2030 fuel mixes.

(scenario E3) leading to a renewable fuel share of 21.3% (E3), or describe a less successful efficiency development and more coal-oriented electricity generation (D2) with a 2030 renewable fuel share of 13.3% (Nitsch 2008, p.128), resulting in direct fuel carbon intensities of 1899.8 and 2093 gCO_2/l_{fuel}[5].

These values correspond roughly with TTW emissions as calculated here for the renewable scenarios D and E (see Table 4.3), although the lower boundary of the scenarios in Nitsch (2008) is even somewhat less carbon intensive than the present scenario E. As well-to-wheel fuel CO_2 intensity scenarios for the BBN, I will

- use the 2030 fuel mix carbon intensity from scenario E, 2600 gCO_2/l, as a lower extreme,
- add the status quo scenario A of roughly 2900 gCO_2/l as a medium scenario, and
- take carbon intensity according to scenario C, 3100 gCO_2/l, as the upper boundary.

Scenarios C and E have been chosen because they span the widest range among the scenarios given in Table 4.3, and it is plausible, though not certain,

[5] The given fuel carbon intensities are not included in the published version of the study. I have received them from the author upon request on January 16, 2009.

that actual well-to-wheel carbon intensity of the 2030 fuel mix will fall into this range. Moreover, the relatively wide range allows to examine within the BBN how much of a difference the choice of fuels in the twenty years to come can make.

As the current EU car CO_2 emission policy does not relate to well-to-wheel emissions, but regulates tailpipe emissions (tank-to-wheel), scenarios for TTW emissions are implemented in the BBN, as well, and can be used for purposes of comparison. For these, (rounded) TTW emissions corresponding to the chosen scenarios E (2000 gCO_2/l), A (2500 gCO_2/l)and C (2600 gCO_2/l) are assumed, as given in Table 4.3.

4.2.1.2 CO_2-Intensity of 2030 Electricity

For transport fuels, today's CO_2 intensity is relatively homogeneous among different countries, varying mainly due to differences in the fraction of diesel. In contrast, electricity CO_2 intensity diverges strongly. According to data provided by Öko-Institut (2004), in 2004, some European countries had CO_2 emissions of less than a hundred gCO_{2equ}/kwh, e.g., Norway (14.5), Switzerland (41.0), or Sweden (76.6). At the upper end of the range, Greece emitted 878.4 gCO_{2equ}/kwh. Germany, emitting 625.4 gCO_{2equ}/kwh in 2005, is among the higher emitters (see Öko-Institut (2007)). These examples show that for electricity, current technology allows for a wide range of CO_2 emission intensity, and possible scenarios for 2030 carbon intensity should not be assumed to lie within too narrow a range.

For German 2030 electricity CO_2 intensity, much will depend on the amount of renewable energies entering the power mix. In a study by Nitsch (2008, p.128), emissions per kwh are given for renewable shares ranging from 49% (scenarios D1 and D2) to 65.2% (scenario E3) in 2030, with the lead scenario lying in between at 53.9% of renewables. Resulting CO_2 emissions range from 263 gCO_2/kwh (E3) to 439 gCO_2/kwh (D2) by 2030[6]. The lead scenario sets 2030 carbon intensity to 336 gCO_2/kwh (Nitsch 2008, p.168). These figures are so-called direct emissions, calculated by relating emissions from energy production at the power plant to the amount of final energy delivered. Overall emissions from electricity production and consumption can be expected to be higher because they include emissions from previous steps (resource extraction, processing, and transport) as well as further emissions from energy distribution. As an example, direct emissions from the German power plant mix in 2005 were 545.6 gCO_{2equ}/kwh (see Öko-Institut (2007)). Comparing this to the overall

[6]This data is not included in the published version of the study. I have received it from the author upon request on January 16, 2009.

emissions of 625.4 gCO_{2equ}/kwh, it can be said that 2005 total emissions were 15% on top of direct emissions, which is not negligible. Thus, an add-on should be considered for electricity emission values taken from Nitsch (2008).

A further study, which examines investment needs and opportunities for making Germany more climate-friendly, proposes that 2030 German emissions from conventional electricity production will be at 675 gCO_2/kwh (Jochem et al. 2008, p.116). A further scenario for 2030 proposes that the emissions from the German power plant mix will be 741.9 gCO_{2equ}/kwh in 2030 (Öko-Institut 2004). As conventional energies are planned to be successively replaced by renewable energies, overall emissions could be substantially lower than these two estimates.

However, very carbon intensive pathways of electricity production are thinkable, as well. Current emissions from German lignite or coal power plants are around 1000 gCO_{2equ}/kwh, depending on the provenience of primary energy carriers. Emissions from lignite from Rhineland reach the maximum level of 1151.4 gCO_{2equ}/kwh (Öko-Institut 2004). Thus, if a 'domestic', non-renewable path should be chosen (not considering technologies for capturing carbon), very high emissions from electricity generation are possible.

Referring to the electricity mix implies that electric energy used for vehicle propulsion shares the characteristics of this mix. However, in a short-term perspective, it could be argued that additional electric energy will not be generated by scaling up the mix, but has to be treated as peak load energy. On the other hand, if electric vehicles are charged overnight, i.e., at times of low energy demand, electric energy used for propulsion rather shares the characteristics of base load energy. Moreover, the possibility of charging (and to some degree discharging) the batteries of electric vehicles overnight might allow dealing with fluctuating flows of renewable energies and therefore promote their use, which might justify treating propulsion energy as largely renewable. The question of what the extra electric energy is made from, of course, has a strong impact on its carbon intensity. Given the large uncertainty on how to account for this, plus the lack of knowlegde on what the German 2030 power plant mix will look like, it seems justified to choose a wide range of scenarios. In the BBN, I will use three scenarios, namely:

- A renewable, low-carbon scenario which is based on the lowest estimate from Nitsch (2008), slightly corrected for up- and downstream emissions: 300 gCO_{2equ}/kwh. In the study, this scenario corresponds to a share of renewables of roughly 65%.

- A status quo scenario, which supposes that the 2030 German power plant mix causes the same emissions as the one of 2005 according to Öko-Institut (2007): 625 gCO_{2equ}/kwh. The corresponding share of renewables in 2005 was 10.3%. Although the share of renewables has already increased, similar electricity CO_2 intensities can also be reached with higher renewable shares, e.g., when combined with high shares of lignite or coal.

- A high-carbon scenario, roughly in the range of today's emissions from German coal and lignite-based electricity: 950 gCO_{2equ}/kwh.

These values are quite similar to those Samaras & Meisterling (2008) use in their assessment of life cycle GHG emissions from plug-in hybrids in the United States: A low scenario of 200 gCO_{2equ}/kwh (based on a mix combining large shares of coal with CCS, nuclear, and renewable energies), the current US emissions of 670 gCO_{2equ}/kwh, and a high emission scenario of 950 gCO_{2equ}/kwh.

Although the scenarios used have been deduced from specific pathways which describe how these emission levels can be reached, in general, similar levels can be obtained in different ways. For example, the low-carbon scenario's emissions could also be achieved by means of fossil energy and carbon capturing. Again, these scenarios are not the only imaginable future paths, but span a plausible range. Any carbon intensity in-between the extremes can be reached in the BBN by attaching appropriate probability weights to the scenarios.

4.2.2 Price Scenarios

In the BBN, market share assessments for the different vehicle types are modeled to depend on the related user costs. The latter include the costs spent on fuel and electricity. The scenarios used for 2030 fuel and electricity prices within the network are deduced in this section.

4.2.2.1 2030 Fuel Prices

According to Mineralölwirtschaftsverband (2009a), the average 2008 fuel price in Germany was 139.7 €ct/l for normal gasoline, 139.9 €ct/l for super gasoline, and 133.5 €ct/l for diesel. By the end of January 2009, prices were lower; super gasoline cost 115.7 €ct/l, and diesel 104.2 €ct/l (Mineralölwirtschaftsverband 2009b). Fuel prices include oil import costs, processing and distribution costs, mineral oil companies' profit margins, and taxes. Current consumer prices include energy taxes of 65.45 €ct/l for gasoline and 47.04 €ct/l for diesel (BMF 2009). Another 19% of value added tax is imposed on the sum of costs, margins and energy taxes.

Tables 4.4 and 4.5 summarize predictions for 2030 gasoline and diesel prices, respectively. The reference scenario by EWI & Prognos (2006) is based on the assumption that the crude oil price will be at 37 $\$_{2000}$/barrel (bbl) in 2030, while the high oil price variant uses the assumption that the 2030 oil price will be at 60 $\$_{2000}$/bbl (EWI & Prognos 2006, pp. 14 and 17). Jochem et al. (2008, p.12) also suppose a 2030 crude oil price of 60 $\$_{2000}$/bbl. Both sources give gasoline and diesel prices in $€_{2000}$. As the base year of my analysis is 2008, 2000 real prices need to be converted to real $€_{2008}$[7]. Prices given in this unit can be found in the third column of Tables 4.4 and 4.5.

Table 4.4: Gasoline Price Projections for 2030

Scenario	Price ($€_{2000}$/l)	Price ($€_{2008}$/l)
EWI reference[1]	1.21	1.39
EWI high oil price[1]	1.39	1.60
Kliminvest[2]	1.43	1.64

Sources: [1]EWI & Prognos (2006, p.15); [2]Jochem et al. (2008, p.13)

Table 4.5: Diesel Price Projections for 2030

Scenario	Price ($€_{2000}$/l)	Price ($€_{2008}$/l)
EWI reference[1]	1.04	1.20
EWI high oil price[1]	1.24	1.43
Kliminvest[2]	1.27	1.46

Sources: [1]EWI & Prognos (2006, p.15); [2](Jochem et al. 2008, p.13)

As can be seen from Tables 4.4 and 4.5, fuel price projections for 2030 discussed so far span a range of 1.20 to 1.46 $€_{2008}$/l for diesel and 1.39 to 1.64 $€_{2008}$/l for gasoline, or roughly 1.30 to 1.55 $€_{2008}$/l when using a half-and-half diesel/gasoline mix.

However, in order to take uncertainties in future projections into account, it may be useful to extend the range of fuel prices covered within the BBN. For

[7]I use the consumer price index given by the Federal Statistical Office Germany for 2000 (92.7) and 2008 (106.6), which results in $1€_{2000}=1.15€_{2008}$ (Statistisches Bundesamt 2009b).

example, in an analysis of electromobility which extends beyond the year 2030, Wietschel & Dallinger (2008, p.11) assume an average fuel price of 1.85 €/l including taxes. Some further insight on upper and lower fuel price boundaries can be gathered from past price development. From 2001 to 2008, the annual average gasoline price in Germany has always been above 1 €/l and rising every year, with an average price of 139.7 €ct/l in 2008. For diesel, the limit of 1 €/l has only been passed as of 2005, but prices have been constantly increasing and have nearly catched up with gasoline prices in 2008, at 133.5 €ct/l (Mineralölwirtschaftsverband 2009a).

To cover a reasonably wide range of possible prices, further price increases should be considered. But prices below current levels should be included, as well, given that fuel prices of more than 1€/l are a rather recent phenomenon in Germany, and given that a large part of the price is made up by taxes and thus is due to political decision. I will use 0.8 $€_{2008}$/l as a lowest estimate in the BBN. As an upper boundary, I will use a price of 2 $€_{2008}$/l, which may be reached, e.g., in case of drastically rising crude oil prices or taxation.

In contrast to the scenarios for CO_2 intensities developed in the previous sections, I will not use three discrete values (low, medium, and high), but enter a discretized continuous probability distribution over fuel prices into the BBN. The reason is that, while fuel prices are important for the outcomes from the BBN, price development is not a central research question the BBN is designed to answer. Therefore, it is preferable to leave room for a wider range of prices under most scenarios, and not to fix them to a specific state under each of them. I will use a distribution which ranges from 0.8 to 2 $€_{2008}/l_{fuel}$. I will put more weight to the center of the distribution, which corresponds to the forecasts from the studies cited above, and make categories and weights roughly symmetric, such that the expected value lies in the central category.

In the BBN, I will use the following 2030 fuel price ranges and weights as a best guess:

- 0.80 – 1.10 $€_{2008}$/l; weight: 5%
- 1.10 – 1.30 $€_{2008}$/l; weight: 15%
- 1.30 – 1.55 $€_{2008}$/l; weight: 60%
- 1.55 – 1.75 $€_{2008}$/l; weight: 15%
- 1.75 – 2.00 $€_{2008}$/l; weight: 5%

In the BBN, weights can be redistributed both through updating and for scenario analysis. For exmple, for analyzing the effect of a high or low fuel price, 100% weight can be set to the highest or lowest range.

4.2.2.2 2030 Electricity Prices and a related Policy Scenario

Electricity prices influence variable costs for driving PHEV and BEV, thus, assumptions on their possible level in 2030 need to be made. It is assumed that vehicles will be charged mainly by private users, i.e., that consumer electricity prices are relevant (as opposed to industry or large-scale consumer prices).

Consumer electricity prices are composed of different components, namely of prices for electricity production, emission-trading induced costs, network access, marketing costs, taxes and further duties, and electricity company gains. Duties currently include, e.g., contributions for the promotion of renewable energies and for combined heat and power generation. In 2005, electricity production made up for roughly 23%, network access for 36%, and taxes and duties for 41% of the consumer electricity price (Wikipedia 2009). Thus, policy issues play an important role in the determination of the overall price. Therefore, a policy scenario for the electricity price will be included in the BBN, which will be developed at the end of this section.

According to Statistisches Bundesamt (2009a), the price of electrical energy for households in Germany was 21.48 €ct/kWh during the first half of 2008 for households consuming between 2500 and 5000 kWh per year.

Compared to 2008 prices, scenarios for 2030 that can be found in the literature predict slightly lower prices. The reference forecast of EWI & Prognos (2006, p.17), e.g., predicts 2030 energy prices for households in Germany of 16.1 €ct_{2000}/kWh. This projection is based on the assumption that the oil price will be 37 $\$_{2000}$/bbl in 2030. In an additional scenario, it is assumed that the 2030 oil price will be at 60 $\$_{2000}$/bbl, which raises the resulting 2030 electricity price slightly to 16.4 €ct_{2000}/kWh (EWI & Prognos 2006, pp.14 and 17). As in the previous section, assessments given in $€_{2000}$ have to be converted to $€_{2008}$. 16.1 €ct_{2000}/kWh corresponds to 18.51 €ct_{2008}/kWh, and 16.4 €ct_{2000}/kWh to 18.86 €ct_{2008}/kWh.

Jochem et al. (2008, p.13) argue that the higher scenario of EWI & Prognos (2006) was still too low, because it would underestimate the costs of CO_2 emission allowances. Assuming that CO_2 costs are completely included, they estimate 2030 electricity to cost 17.31 €ct_{2000}/kWh (i.e., 19.91 €ct_{2008}/kWh). In their study, a price maximum of 18.03 €ct_{2000}/kWh is reached in 2010, and then prices decline gradually.

For analyzing the capital value of electromobility concepts, Wietschel & Dallinger (2008, p.11) assume an electricity price of 19 €ct/kWh.

In summary, the lowest estimate is the EWI & Prognos (2006) reference forecast of 18.51 €ct_{2008}/kWh, and the highest one is the prediction by Jochem et al. (2008) of 19.91 €ct_{2008}/kWh. For the BBN, I will use electricity prices of 18.50 to 20 €ct_{2008}/kWh as a central estimate, and give a high weight to this range.

As forecasts found in the literature lie within a small price range, I will choose additional price ranges to be considered in the BBN in a somewhat extreme way. The aim is to generate a greater range of assessments in order to account for the uncertainty underlying price estimates 20 years from now. Above the central price range, a higher range of 20 to 21.50 €ct_{2008}/kWh will be used, the upper limit of which is today's electricity price. Moreover, an even higher range of up to 25 €ct_{2008}/kWh will be included, with a low weight. The rationale behind this is that there are many factors which could drive up electricity prices in the 20 years to come. For example, if the peak oil hypothesis turned out to be true, the increasing scarcity of oil could have an impact on electricity prices. Or network costs could rise strongly because of the need to accommodate for fluctuating renewable energy, and to replace it with other kinds of energy in low production phases. As network costs make up for a substantial share of overall energy costs, this could increase total costs substantially. Another example is that, in case much additional electric energy was required for transportation, less favorable locations or resources could be needed for producing enough energy, which could drive up marginal and thus average costs. Another contribution could come from additional energy taxes for electric vehicle energy, in analogy with the German energy tax added to fuels today (65.45 €ct/l or 7.3 €ct/kWh for gasoline and 47.04 €ct/l or 4.7 €ct/kWh for diesel). This measure would follow the assumption by Wietschel & Dallinger (2008, p.11) that a tax on electricity for traffic will be levied in order to make sure that all drivers contribute to road infrastructure expenditures. There are many reasons why prices could rise, and there is no way to know for certain which ones will or will not occur and by how much they may raise overall electricity prices. The choice of 25 €ct/kWh is made arbitrarily in order to extend the present assessment to a larger range of thinkable futures.

The price distribution is extended by adding similar ranges below the central price estimate. Again, the reason is that different causes could drive electricity prices in this direction, as well. For example, renewable energies may bear a chance of reducing prices, and current energy taxes levied for their promotion may be reduced over time. Electromobility and connected vehicle-to-grid services might also lead to declining prices over time, to name just a few possible drivers. Thus, it seems plausible to extend the considered price range at the lower end, as well.

Finally, an extremely low price case is considered as a policy scenario. As explained, taxes and duties sum up to roughly 40% of electricity prices. I consider that as an incentive policy, taxes and duties may be dropped for electricity used for mobility. Starting from a medium electricity price of 20 €ct_{2008}/kWh, substracting 40% results in a price of 12 €ct_{2008}/kWh. Of course, the described policy is just one way in which a similar price could be reached, and assessing this possibility is not linked to any specific cause in the BBN model.

As for fuel prices, a discretized continuous probability distribution over electricity prices is used in the BBN. Again, the idea is to allow for a wide range of prices under most scenarios. The following categories and initial weights are chosen:

- 12 €ct_{2008}/kWh; policy scenario
- 13.5 to 17 €ct_{2008}/kWh; weight: 5%
- 17 to 18.5 €ct_{2008}/kWh; weight: 15%
- 18.5 to 20 €ct_{2008}/kWh; weight: 60%
- 20 to 21.5 €ct_{2008}/kWh; weight: 15%
- 21.5 to 25 €ct_{2008}/kWh; weight: 5%

In the BBN, the policy scenario of 12 €ct_{2008}/kWh is implemented via an electricity price policy node which sets the electricity price node to that state when activated. Otherwise, the weight of this value in the distribution is set to zero.

4.2.3 Battery Development Scenarios

The development of batteries, especially in regard to energy density and costs, is an important factor for the applicability of battery electric vehicles (BEV) or plug-in hybrid electric vehicles (PHEV). At today's energy densities, the weight and volume of batteries needed is very large, and at today's costs, high energy batteries are too expensive for BEV or PHEV with major electric ranges to be competitive. This section deals with scenarios for the development of these parameters over the 20 years to come. It is assumed that 2030's standard battery for use in vehicles will be a lithium-ion (Li-ion) battery, as this battery type currently provides the highest energy density and is able to provide high power (Eurobat 2005, p.6, p.26). Moreover, Li-ion batteries offer large potential for further improvement. While, e.g., for fuel and electricity CO_2 intensity, it was important to focus on assessments relating to Germany, this is not the case for battery development, as the battery market is of global nature.

4.2.3.1 2030 Battery Prices

Current batteries for PHEV or BEV applications are quite costly. Lemoine et al. (2008, p.8) point out that current battery packs for PHEV (including electronics) may well cost more than 1000 $/kwh. Axsen et al. (2008, p.12) state that current costs for advanced batteries fall in the range of 800 $/kwh to 1000 $/kwh, an assessment they base on Pesaran et al. (2007).

While different authors agree that prices are likely to decrease in the future, it is difficult to come to an assessment of what level they may have reached by 2030. This is partly due to the fact that price development will depend on the production volume of batteries, which is unknown, as well. Some estimates are available for the possible price development for the nearer future. For example, Concawe et al. (2007, p.62) assume that lithium-ion (Li-Ion) battery prices will be at 600 €/kwh by 2010.

Kalhammer et al. (2007) have examined advanced battery technologies with a potential to be fully developed and available for use in HEV, full performance BEV, and PHEV within the 5 to 10 years to come. Thus, their statements relate roughly to 2015. They find that battery costs decrease both with increasing production rates and with increasing cell size. Table 4.6 gives some of their results for full performance BEV, PHEV-40, i.e., plug-in hybrids with an electric range of 40 miles, and full HEV.

Table 4.6: Cost Projections for Li-Ion Batteries

Vehicle type	Batt. Capacity (kWh)	Module Cost at 500 MWh/year ($/kWh)	Module Cost at 2500 MWh/year ($/kWh)
BEV	40	285	195
PHEV-40	14	380	260
HEV	2	805	550

Source: Kalhammer et al. (2007, p.47)

Apart from estimates for the nearer future, longer-term battery development is often described in the form of goals, where it is left open by when these goals can be reached. In a recent report, the Association of European Storage Battery Manufacturers (Eurobat) specifies the research and technological development needs for battery systems over the next 10 to 15 years. Eurobat's strategic research agenda for Li-Ion batteries focusses on the objective to bring down costs from the current level of 700 to 1500 €/kwh to 200 €/kwh (Eurobat 2005, p.36).

The US Advanced Battery Consortium (USABC) specifies goals for advanced batteries for EV as follows. The 'minimum goal for long term commercialization' is that the selling price should drop below 150 \$/kWh when 25,000 units at 40 kWh have been sold. The 'long term goal' is a price of 100 \$/kWh (USABC 2009a). For PHEV, the goals for batteries with a high energy-to-power ratio include that the available energy when depleting the battery should be 11.6 kWh, and the maximum system production price at $100,000$ units per year should be 3400 \$, which results in a price of 293 \$/kWh (USABC 2009b).

According to Axsen et al. (2008, p.6), USABC goals are 300 \$/kWh for PHEV-10 and 200 \$/kWh for PHEV-40, i.e., for PHEV with all-electric ranges of 10 or 40 miles, respectively. These figures relate to costs at the level of battery original equipment manufacturers (OEM), and to get an impression of consumer prices, Axsen et al. (2008, p.11) estimate that a markup of 25 to 33% has to be added.

In different studies, scenarios for battery price development have been used. Wietschel & Dallinger (2008) describe a scenario where the German car fleet is nearly completely substituted with hybrid and electric vehicles by the year 2050, the so-called dominance scenario. This scenario implies that Li-Ion batteries successively reach a target price of 200 to 300 €/kwh (Wietschel & Dallinger 2008, p.12). A table shows that battery capacity of PHEV and City-BEV is assumed to be 14 kWh and 20 kWh, and that the respective battery costs in the year 2030 are 4710 € and 6729 € (Wietschel & Dallinger 2008, p.15). It results that for 2030, battery prices of 336 €/kWh are assumed.

Jochem et al. (2008, p.93) include an optimistic scenario that assumes battery prices to decrease from 1000 €/kWh to 200 €/kWh by 2030.

In their analysis of economic and environmental benefits of PHEV, Shiau et al. (2009) assume base battery capacity costs, which include the full costs of adding battery capacity to vehicles, to be 1000 \$/kwh. They use a low battery cost scenario of 250 \$/kwh for sensitivity analysis.

Among the different values given for current prices, development aims, and development scenarios, it is hard to identify suitable candidates for 2030 battery price scenarios to be used in the BBN. Already current price estimates span a wide range, with the Eurobat assessment of 700 to 1500 €/kWh being the most extended one. Thus, while 1500 €/kWh would be a candidate for an upper battery price limit, all other studies cited give lower prices already for today. At a price of 1500 €/kWh, PHEV with considerable electric ranges and BEV will be much too expensive for acquiring substantial market shares, which makes much of the BBN analysis pointless. Instead, as an upper limit of 2030 battery prices, 600 €/kWh is chosen. This figure corresponds to the assessment of Concawe et al. (2007) for 2010 battery prices. Assuming this price for 2030 implies that there will be a certain decline of battery prices in the 20 years to come, but a modest one. All other battery price estimates for years between 2015 and 2030 as well as development aims cited above are much lower.

As a lower boundary of 2030 battery prices, a value of 200 €/kWh is chosen. This corresponds to the Eurobat (2005) development aim for about 2020, and to the 2030 battery price assumed by Jochem et al. (2008), but is lower than most other estimates (except from USABC (2009a) EV battery development goals, which are still lower). It is useful to choose a relatively low value in order to be able to span a wide range of possible prices, and in order to be able to implement an optimistic scenario within the BBN.

Although costs may vary for PHEV and BEV, and in fact some of the studies give different prices for the two applications, these two scenarios will be used for both PHEV and BEV within the BBN. This is done in order to keep the complexity of the BBN down to a manageable size.

In summary, for the purposes of the BBN, the following battery price scenarios (as well as mixtures thereof), are considered:

- High price: 600 $€_{2008}$/kWh, and
- low price: 200 $€_{2008}$/kWh.

4.2.3.2 2030 Battery Energy Density

Battery energy density, also called specific energy, is the amount of energy that can be stored in a battery of a unit weight (it can also be expressed per unit of volume). It is a decisive parameter for PHEV and BEV success, because given that cars can carry a battery of limited volume and weight only, it influences their (electric) range. Today, further improvement in battery energy density is commonly seen as a prerequisite for the success of PHEV and BEV.

Samaras & Meisterling (2008, p.3171) find that current Li-ion batteries have energy densities of 80 to 120 Wh/kg. According to Eurobat (2005, p.36), state of the art Li-ion batteries have an energy density of 100 to 120 Wh/kg. In their overview of battery technologies, they state a specific energy of 90 Wh/kg for high power Li-ion batteries, and of 125 Wh/kg for high energy Li-ion batteries (Eurobat 2005, p.8).

Burke (2007, p.809) lists current Saft Li-ion batteries for HEV applications with an energy density of 77 Wh/kg, and for EV with a density of 140 Wh/kg, while Axsen et al. (2008, p.15) describe a JCS Li-ion battery for use in PHEV which has an energy density of 94 Wh/kg.

As for battery costs, projections for the development of battery energy density are rare, but there exist goals. Axsen et al. (2008) have assembled goals or requirements for PHEV batteries by different authors. According to their list, the USABC has set forward a goal of 100 Wh/kg for PHEV-10 batteries and of 140 Wh/kg for PHEV-40 batteries (Axsen et al. 2008, p.7). Other studies cited in their table require somewhat lower energy densities, the lowest being 40 Wh/kg for a PHEV-20 demanded in a study by the Electric Power Research Institute (Graham 2001).

For advanced batteries to be used in electric vehicles, the USABC sets higher targets of 150 Wh/kg as a 'minimum goal for long term commercialization', and 200 Wh/kg as a 'long term goal' (USABC 2009b).

In their life-cycle analysis of new car technologies, Weiss et al. (2000, pp.1-15) assume that the former target of 150 Wh/kg can be reached by 2020 and assess the characteristics of battery electric vehicles accordingly.

The most optimistic objective is that by Eurobat (2005, p.36): In their Li-ion strategic research agenda, they set forward the aim of reaching 300 Wh/kg.

In the present BBN, two specific energy scenarios for 2030 will be applied, namely

- a lower estimate of 120 Wh/kg, which is roughly the upper limit of today's Li-ion battery energy density, and
- a higher estimate of 200 Wh/kg.

The higher value corresponds to the USABC long term goal, as well as to the assessment of many experts of what is possible for Li-ion batteries and needed for successful BEV commercialization.

4.2.4 Daily Driving Distances

In order to decide what is a useful electric range for PHEV, and a useful range for BEV, it is important to know how far drivers want to travel between two charges of the battery. This, of course, depends on how often the battery is charged. For the present purposes, I assume that PHEV and BEV are charged once a day, most likely during the night, where vehicles are parked long enough for a complete recharge. If vehicles can be charged more often, e.g., if commuters drive to work, recharge their vehicles there, then drive back home and plug them in again, the daily distance driven in electric mode can be increased considerably. However, it is also possible that consumers are unwilling or unable to plug in their vehicle every night. These aspects call for further research into consumer behaviour.

Assuming that PHEV and BEV are fully charged once a day, the question of whether they can cover their common daily driving distance with one charge (BEV) or the question of what share of the distance they travel can be covered in electric mode (PHEV) depends on driving profiles.

Table 4.7: Distribution of Distances Driven in a Day

Class i	Distance Range (km)[1]	Share of Drivers (%)[1] $s_{d,i}$	Mean Distance (km)[2] md_i	Share Driven by Class (%)[2] $s_{km,i}$
1	≤1	1	1	0.02
2	2 –4	7	3	0.4
3	5–10	15	7.5	2.2
4	11–20	19	15.5	5.8
5	21–50	30	35.5	20.8
6	51–100	17	75.5	25.1
7	≥101	11	212	45.6

Sources: [1]DIW & Infas (2003, p.150); [2]Own calculation

For the BBN, I will use a distribution derived from a study on mobility in Germany by DIW & Infas (2003, p.150), and assume that driving behavior in Germany is roughly constant over time. The source gives a distribution of what shares of car drivers have travelled how far on a given day, displayed in the second and third column of Table 4.7. In the study, car drivers are defined as persons who mainly have used a car that day, as compared to persons mainly walking, biking, or using public transport. Unfortunately, this data is not as recent and not as exact as one would like it to be. It relates only to one given day instead of depicting average driving behaviour. Moreover, driving distances are given in classes (up to 1 km; 2 to 4 km;...), and the upper boundary of kilometers driven per day is not given, as the highest class is just ‘more than 100 km’. Still, this is the best data currently available for Germany. I have decided to use the mean distance within each class for deriving a distribution that depicts what share of the overall distance driven has been contributed by the different classes of drivers. As the upper boundary for the highest class is missing, the respective mean distance, md_7, was calculated from the values given for the shares of drivers in each class i, $s_{d,i}$, and the mean distance driven by drivers of the other classes, $md_{i,i=1,...,6}$ given in Table 4.7, as well as the mean distance driven by any driver, which was given as $md = 51.1$ km in the study. The mean distance for the highest class results as

$$md_7 = \frac{100 * md - \sum_{i=1,\ldots,6} s_{d,i} * md_i}{s_{d,7}} = 212 \text{ km}.$$

The share of overall kilometers contributed by a class i of drivers, $s_{km,i}$, is calculated as

$$s_{km,i} = \frac{s_{d,i} * md_i}{\sum_{j=1,\ldots,7} s_{d,j} * md_j}.$$

For the results, see the last column of Table 4.7. Mean distances and shares of overall kilometers contributed by each class as listed in the Table are used for determining the share PHEV drive in electric mode. In the BBN, for each class of drivers, it is checked whether the electric range of PHEV suffices for covering the mean distance driven in a day, and if not, what share of daily distance will exceed the electric range and thus be covered in combustion engine mode. These shares are weighed with the share of overall kilometers driven by drivers of the respective class.

Using class mean kilometrage tends to result in too optimistic electric driving shares for PHEV. In the model, the PHEV electric driving share is a full 100% whenever PHEV electric range is equal to or greater than 212 km, the mean distance driven by the farthest driving class of drivers. This is unrealistic, because there are drivers who drive much further in a day. Similar problems arise with using mean distances for any class of drivers the upper limit of the distance range of which lies above PHEV electric range. In the absence of more exact data on how far car owners in Germany drive in a day, this modelling approach is used as a proxy, but better data would clearly improve results here.

4.2.5 EU Car CO_2 Regulation

In December 2008, the European Parliament has adopted a car CO_2 regulation, based on a proposal by the European Commission (European Commission 2009b). The aim of the regulation is to reduce the fleet average CO_2 emissions of all newly registered cars in the EU to 130 g/km by 2012. In fact, the original aim of regulation was to reach EU new car fleet CO_2 emissions of 120 g/km by 2012, and the agreed regulation of 130 g assumes that a further 10 g is saved through biofuels.

The details of the regulation are as follows:

- Specific CO_2 targets for individual cars: A so-called limit value curve allows higher emissions for heavier cars. The formula for the curve is: Specific car CO_2 emissions (g/km) $= 130 + 0.0457(M - 1372)$, where M is the mass of the respective vehicle in kg (European Commission 2009a).

- Phasing-in: Initially, only a share of each manufacturer's new vehicles must comply with the above curve, on average. That share is 65% in 2012, 75% in 2013, 80% in 2014, and 100% from 2015 on.

- Penalty payments for excess emissions: Manufacturers have to pay a premium for each gram of CO_2 their fleets emit in exceedance of the limit value, multiplied by their numbers of new cars sold. Until 2018, the penalty is 5 € per new car for the first gCO_2/km of exceedance, 15 € for the second, 25 € for the third, and 95 € for each subsequent gCO_2/km. From 2019, any gram of exceedance will cost 95 € per new car.

The regulation also sets a longer-term target of 95 gCO_2/km for the European new car fleet from the year 2020 on. The details of that second regulatory step have been left up to a review that is planned to be completed by the beginning of 2013 (European Commission 2009b).

The details of this second step may be very influential in regard to 2030 new car fleet CO_2 emissions. On the one hand, it is still possible, e.g., that details can not be agreed on and no tightening beyond the 130 gCO_2 regulation takes place, or that a very generous limiting value curve is designed, or that penalties for the second step will be negligibly low. On the other hand, a strict interpretation of the 95 gCO_2/km goal is conceivable, as well. For the BBN, I will therefore use different scenarios for a 2020 regulation in order to analyze the impact experts assign to each of them. In doing so, I mainly stick to the current EU logic of prescribing tailpipe emissions of cars, i.e., tank-to-whell (TTW) emissions. This approach has brought about intensive debate on how much of those emissions could be avoided by switching to less CO_2-intensive biofuels or blends. An approach that avoids this debate is to regulate fuel economy instead of tailpipe emissions, as done in the US with the standards on miles per gallon (mpg) cars have to achieve. However, for Europe it currently seems most likely that the TTW approach will be maintained.

A first option considered in the BBN is that no 2020 regulation is agreed on. In that case, the first step of regulation described above, limiting emissions to 130 gCO_2/km by 2012 to 2015, is assumed to be the only EU fuel consumption policy in place by 2030. Given that tank-to-wheel CO_2-intensity of the current fuel mix is roughly 2470 gCO_2/l[8], this relates to a fuel consumption of roughly 5.25 l/100km.

A second variant is that a 95 gCO_2/km limit will be decided for 2020. Assuming that this target is interpreted in a generous way, 20 g may be dis-

[8]Calculated as 0.58 * 71 $gCO_2/MJ_{\text{gasoline}}$ * 32.2 MJ/l_{gasoline} + 0.42 * 76 gCO_2/MJ_{diesel} * 35.8 MJ/l_{diesel}, values taken from Tables 4.1 and 4.2.

counted on behalf of biofuel use by 2030, such that the target to be met by cars alone would be 115 gCO_2/km TTW. This equals a fuel consumption of roughly 4.65 l/100km at the current fuel mix. Details of the regulation can be imagined in analogy to the first step of regulation, i.e.,

- The limiting value curve for 2020 and beyond then is: Specific car CO_2 emissions (g/km) $= 115 + 0.0457(M - 1372)$, where M is the mass of the respective vehicle (in kg).
- Again, there is a phasing-in over three years, such that the share of each manufacturer's fleet that must comply is 65% in 2020, 75% in 2021, 80% in 2022, and 100% from 2023 on.
- There also is a phase of lower penalties for smaller excess emissions, as in the first step of regulation. Payments for exceeding the limit are 5 €$_{2008}$ per new car for the first gCO_2/km of exceedance, 15 €$_{2008}$ for the second, 25 €$_{2008}$ for the third, and 95 €$_{2008}$ for each subsequent gCO_2/km until 2025. From 2026 on, it is 95 €$_{2008}$ per new car for any gram of exceedance.

In the BBN, a third version of a 2020 EU regulation is considered that demands car manufacturers to make the whole step of improvement from 130 to 95 gCO_2/km on the car and engine side, without the option of relegating some of the emission reduction to the fuel side. With today's fuel mix, this relates to a consumption of about 3.85 l/100km. Decreases in fuel carbon content would lead to emission reductions beyond 95 gCO_2/km. The details of the third scenario considered are as follows:

- The limiting value curve for 2020 and beyond is: Specific car CO_2 emissions (g/km) $= 95 + 0.0457(M - 1372)$, with M the mass of the respective vehicle (in kg).
- The phasing-in is as in the second variant.
- Penalties are defined as in the second variant.

As a fourth regulation scenario, it is assumed that 95 gCO_2/km have to be achieved, but considering not only tailpipe emissions, but including greenhouse gases emitted in the fuel life cycle from resource extraction to burning fuel, i.e., well-to-wheel (WTW) emissions. 95 gCO_2/km WTW relates to a fuel consumption of 3.25 l/100km at current fuel mix. Details of the regulation are as in the above versions.

A more general regulation approach would be not to limit fuel consumption, but energy consumption (kWh/km or MJ/km), as this would extend to electric propulsion, as well. However, in regard to battery electric vehicles, this regulation will not be binding in most cases, as electric vehicles are more energy efficient than combustion engine vehicles. The 2470 gCO_2 contained in one liter of current fuel relate to 33.7 MJ of energy it contains, or 9.4 kWh (3.6MJ $\widehat{=}$ 1kWh). 95 gCO_2/km thus translates to 360 Wh/km, which would be the equivalent of the 2020 regulation in terms of energy consumption per km. As an example, the Tesla Roadster, an electric sports car, consumes 110 Wh/km (Tesla Motors 2009). As another example, the range of energy consumption figures for BEV proposed in the BBN is 100 to 400 Wh/km, as will be discussed later (see Section 4.4.3.4).

4.2.6 Annual Cost Increments of PHEV and BEV over ICE

In the BBN, sales shares of different vehicle types are modeled conditional on annual user cost differences, because it is assumed that costs are the most important argument consumers base their choice on. Annual user costs include depreciation of the initial investment as well as variable costs, i.e., fuel or electricity costs. It is assumed that maintenance costs are roughly the same for ICE, PHEV and BEV and thus do not have to be treated here, because sales share are modeled to depend on cost differences.

Depreciation is implemented as an annual depreciation rate r times purchase costs. Purchase cost differences for PHEV and BEV compared to ICE are calculated within the BBN. They consist of the cost differences of the vehicles themselves, plus the expenses for the batteries needed for PHEV and BEV. It is assumed that the battery lasts over the whole vehicle lifetime, such that the battery costs are incurred only once. For the details of the calculation of vehicle cost increments, see Section 4.3.

The depreciation rate is deduced from assumptions on vehicle lifetime. According to the German Federal Motor Transport Authority (KBA), the average age of vehicles taken out of service in Germany is roughly 12 years (KBA 2009a, pp.4f). In the decade from 1997 to 2006, it rose from 11.5 to 12 years. The average age of vehicles signed off the register was 11.9 years throughout 2002 to 2004, and 12 years in 2005 and 2006. A recent incentive provided in Germany, the so-called scrapping bonus of 2500 € which has been payed to anyone who scrapped a car of 9 years and older when buying a new vehicle in 2009, may have reduced the average age of vehicles taken out of service in 2009, but this is only a short-term effect. For the BBN, it is assumed that average useful life of vehicles will be $n = 12$ years in the period of interest. As the BBN is built to assess 2030 sales, this means that car buyers in 2030 will assume a useful life span of 12 years for their newly bought vehicles. Finally, it is assumed that the interest rate is $i = 0.05$. The annual depreciation rate r can now be calculated as

$$r = -K \frac{(1+i)^n i}{(1+i)^n - 1},$$

where K, the purchase cost, is set to $K = -1$ in order to get r to represent the fraction of costs to be amortized each year (see Rommelfanger (1999, p.93)). It results that $r = 0.1128$.

Moreover, the distance driven in a year is needed as an input to the BBN, where it will be combined with fuel or energy consumption and prices in order to yield annual variable costs.

Following Kalinowska & Kunert (2009, p.875), in the years from 1994 to 2008, German passenger vehicles have been driven between 12600 and 14300 km per year (from 1994 to 2004, figures are only given for every second year). The lowest value was reached in 2006, the highest in 2007. In 2008, passenger vehicles travelled an average 14100 km. As an upper boundary, annual kilometrage in 2030 is assumed to be 15000 km per car and year.

Both the annual depreciation rate and the annual kilometers travelled enter into the BBN nodes which determine annual cost differences of PHEV and BEV to ICE.

4.2.7 Emissions from Other Car Types

Apart from ICE, PHEV and BEV, which are explicitly modelled, a catch-all variable 'other vehicle types' is included in the BBN when it comes to sale shares. This has been done to leave some room for experts to assign sales shares to technologies not explicitly modeled. However, this variable plays the role of an indicator rather than representing other technologies in an appropriate way. In case an expert assigns large sales shares to this variable, it shows that the BBN is not able to sketch his or her view of the 2030 car market in a reasonable way. The initial assumption is that experts will assign only minor market shares to other technologies. In order to come up with an assessment of fleet CO_2 emissions, however, an assumption about CO_2 emissions from other cars has to be made. For avoiding to make the network even more complex, I have chosen to take the maximum emissions of ICE, PHEV and BEV and assign them to other vehicles. This makes sure that these vehicles are related to emissions which are not off the range of possible car emissions in 2030, and that they do not draw down fleet emissions. For a more realistic approach, it would be necessary to ask experts what other technologies they can imagine, and then to build them into the BBN explicitly, which would result in tremendous extra complexity. However, the first interview round has revealed that experts asked at that point did not expect any other vehicles to acquire meaningful market shares over the time horizon of the investigation.

4.3 Documentation of Calculative Nodes

In the BBN, nearly half of the nodes (21 out of 46, the grey-colored nodes in Figures 4.1 and 4.2) are calculative nodes which are computed within the network. Each calculative node contains an equation which prescribes how its probability table is calculated from tables stored in other nodes. In this section, equations for all calculative nodes are presented. Equations are given in the order nodes are arranged in the graphical model in Figure 4.1, from top to bottom and left to right. Experts were allowed to make changes to the BBN structure, such that in some cases some equations were changed during elicitation to adapt the network.

In the present documentation of equations, abbreviations for the variable names in the BBN are used. Abbreviations have been chosen such that in most cases, relating them to the original names is straightforward. To avoid confusion, a full list assigning the short names of variables used in the equations to their names as displayed in the BBN graphics is provided in Table 4.8.

Table 4.8: Abbreviations for Calculative Nodes

(Table continued on next page)

Abbreviation	Node Name in the BBN
BatEnDens	Battery Energy Density (kWh/kg)
BatCost	Battery Costs 2030 (€/kWh)
PHEVBatEn	PHEV Battery Energy (kWh)
BEVBatEn	BEV Battery Energy (kWh)
PHEVBatWeight	PHEV Battery Weight (kg)
BEVBatWeight	BEV Battery Weight (kg)
ICEFuelCons	ICE Average Fuel Consumption 2030 (l/100km)
PHEVFuelCons	PHEV Average Fuel Consumption 2030 (l/100km)
PHEVEnCons	PHEV Energy Consumption 2030 (kWh/100km)
BEVEnCons	BEV Energy Consumption 2030 (kWh/100km)
ICECostIncr	ICE 2030 Cost Increment (€/Car)

Abbreviation	Node Name in the BBN
PHEVCostIncr	PHEV 2030 Cost Increment (€/Car)
BEVCostIncr	BEV 2030 Cost Increment (€/Car)
PHEVElds	PHEV Electric Driving Share (%)
PHEVElRange	PHEV Electric Range (km)
BEVRange	BEV Range (km)
FuelPrice	Fuel Price 2030 (€/l)
ElPrice	Electricity Price 2030 (€/kWh)
ICEVarCost	ICE Fuel Costs (€/100km)
PHEVVarCost	PHEV Variable Costs (€/100km)
BEVVarCost	BEV Energy Costs (€/100km)
PHEVBatCost	PHEV Battery Costs (€)
BEVBatCost	BEV Battery Costs (€)
ConsInc	Consumer Incentive BEV & PHEV (€/Car)
PHEVAnnCostD	PHEV Annual Cost Difference to ICE (€)
BEVAnnCostD	BEV Annual Cost Difference to ICE (€)
ICETotal	Total Relative Sales ICE
PHEVpICE	PHEV Sales per 100 ICE Sales (No. of Cars)
BEVpICE	BEV Sales per 100 ICE Sales (No. of Cars)
OtherpICE	Other Sales per 100 ICE Sales (No. of Cars)
ICEShare	ICE Sales Share 2030 (%)
PHEVShare	PHEV Sales Share 2030 (%)
BEVShare	BEV Sales Share 2030 (%)
OtherShare	Other Sales Share 2030 (%)
WTWorTTW	WTW or TTW (i.e., Well-to-Wheel or Tank-to-Wheel)
TTWCO2	TTW CO_2 Intensity of Fuel (gCO_2/l)
WTWCO2	WTW CO_2 Intensity of Fuel (gCO_2/l)
ElCO2	CO_2 Intensity of Electric Energy (gCO_2/kWh)
ICECO2em	ICE CO_2 Emissions (gCO_2/km)

Abbreviation	Node Name in the BBN
PHEVCO2em	PHEV CO_2 Emissions (gCO_2/km)
BEVCO2em	BEV CO_2 Emissions (gCO_2/km)
FleetCO2em	2030 New Car Fleet Emissions (gCO_2/km)
	(Table continued from previous page)

Most equations are self-explaining. For example, ICE variable costs (ICE-VarCost), i.e., fuel costs are calculated as the product of ICE fuel consumption per unit distance and the fuel price. Some equations are based on extra information or assumptions. The share PHEV drive in electric mode (PHEVElds) depends on how far the vehicle is driven between two charges of the battery, annual user cost differences for PHEV and BEV compared to ICE (PHEVAnnCostD and BEVAnnCostD) are calculated on the base of assumptions on useful vehicle lifetime and kilometers traveled annually, and fleet CO_2 emissions (FleetCO2em) need an assessment of emissions from vehicles other than ICE, PHEV or BEV. The assumptions are not explained here, but have been presented and discussed in the previous Section 4.2. Finally, in some equations, factors of 100 or $10,000$ are used. They have been added to convert results to the units usually used. Units for all variables can be found in Table 4.8. Equations for the nodes are as follows.

$$
\begin{aligned}
\text{PHEVBatWeight} &= \frac{\text{PHEVBatEn}}{\text{BatEnDens}} \\
\text{BEVBatWeight} &= \frac{\text{BEVBatEn}}{\text{BatEnDens}} \\
\text{PHEVElRange} &= \frac{\text{BatEnDens} * \text{PHEVBatWeight}}{\text{PHEVEnCons}} * 100 \\
\text{PHEVElds} &= 0.02 * \min((\text{PHEVElRange}/1), 1) \\
&\quad +0.4 * \min((\text{PHEVElRange}/3), 1) \\
&\quad +2.2 * \min((\text{PHEVElRange}/7.5), 1) \\
&\quad +5.8 * \min((\text{PHEVElRange}/15.5), 1) \\
&\quad +20.8 * \min((\text{PHEVElRange}/35.5), 1) \\
&\quad +25.1 * \min((\text{PHEVElRange}/75.5), 1) \\
&\quad +45.6 * \min((\text{PHEVElRange}/212), 1)
\end{aligned}
$$

$$
\begin{aligned}
\text{BEVRange} &= \frac{\text{BatEnDens} * \text{BEVBatWeight}}{\text{BEVEnCons}} * 100 \\
\text{ICEVarCost} &= \text{ICEFuelCons} * \text{FuelPrice} \\
\text{PHEVVarCost} &= (\text{PHEVElds} * \text{PHEVEnCons} * \text{ElPrice} \\
&\quad +(100 - \text{PHEVElds}) * \text{PHEVFuelCons} \\
&\quad *\text{FuelPrice})/100 \\
\text{BEVVarCost} &= \text{BEVEnCons} * \text{ElPrice} \\
\text{PHEVBatCost} &= \text{PHEVElRange} * \text{PHEVEnCons} * \text{BatCost} \\
\text{BEVBatCost} &= \text{BEVRange} * \text{BEVEnCons} * \text{BatCost} \\
\text{PHEVAnnCostD} &= (-\text{ICECostIncr} + \text{PHEVCostIncr} + \text{PHEVBatCost} \\
&\quad -\text{ConsInc}) * 0.1128 \\
&\quad +(-\text{ICEVarCost} + \text{PHEVVarCost}) * 150 \\
\text{BEVAnnCostD} &= (-\text{ICECostIncr} + \text{BEVCostIncr} + \text{BEVBatCost} \\
&\quad -\text{ConsInc}) * 0.1128 \\
&\quad +(-\text{ICEVarCost} + \text{BEVVarCost}) * 150 \\
\text{ICETotal} &= 1 \\
\text{ICEShare} &= \frac{\text{ICETotal}}{\frac{\text{PHEVpICE}}{100} + \frac{\text{BEVpICE}}{100} + \frac{\text{OtherpICE}}{100} + \text{ICETotal}} * 100 \\
\text{PHEVShare} &= \frac{\frac{\text{PHEVpICE}}{100}}{\frac{\text{PHEVpICE}}{100} + \frac{\text{BEVpICE}}{100} + \frac{\text{OtherpICE}}{100} + \text{ICETotal}} * 100 \\
\text{BEVShare} &= \frac{\frac{\text{BEVpICE}}{100}}{\frac{\text{PHEVpICE}}{100} + \frac{\text{BEVpICE}}{100} + \frac{\text{OtherpICE}}{100} + \text{ICETotal}} * 100 \\
\text{OtherShare} &= \frac{\frac{\text{OtherpICE}}{100}}{\frac{\text{PHEVpICE}}{100} + \frac{\text{BEVpICE}}{100} + \frac{\text{OtherpICE}}{100} + \text{ICETotal}} * 100
\end{aligned}
$$

$$
\begin{aligned}
\text{ICECO2em} &= \text{if WTWorTTW} == \text{WTW} \\
&\quad \text{then ICEFuelCons} * \text{WTWCO2}/100 \\
&\text{else ICEFuelCons} * \text{TTWCO2}/100
\end{aligned}
$$

$$
\begin{aligned}
\text{PHEVCO2em} &= \text{if WTWorTTW} == \text{WTW} \\
&\quad \text{then } ((100 - \text{PHEVElds}) * \text{PHEVFuelCons} \\
&\qquad\quad * \text{WTWCO2} \\
&\qquad\quad + \text{PHEVElds} * \text{PHEVEnCons} * \text{ElCO2})/10000 \\
&\text{else } ((100 - \text{PHEVElds}) * \text{PHEVFuelCons} * \text{TTWCO2} \\
&\qquad + \text{PHEVElds} * \text{PHEVEnCons} * \text{ElCO2})/10000
\end{aligned}
$$

$$
\text{BEVCO2em} = \text{BEVEnCons} * \text{ElCO2}
$$

$$
\begin{aligned}
\text{FleetCO2em} &= (\text{ICEShare} * \text{ICECO2em} \\
&+\text{PHEVShare} * \text{PHEVCO2em} \\
&+\text{BEVShare} * \text{BEVCO2em} \\
&+\text{OtherShare} \\
&*\max(\text{ICECO2em}, \text{PHEVCO2em}, \text{BEVCO2em}))/ \\
&(\text{ICEShare} + \text{PHEVShare} + \text{BEVShare} + \text{OtherShare})
\end{aligned}
$$

4.4 Expert Elicitation of Conditional Probabilities

Within the BBN, conditional probabilities for twelve nodes (the beige colored nodes in Figures 4.1 and 4.2) have to be provided through elicitation. These twelve nodes provide the substance for the present analysis, while the nodes presented in the previous sections serve either as inputs for elicitation and for scenario analysis (e.g., policy and technological development scenarios), or for processing elicitation results (calculative nodes).

Experts are asked to give conditional probabilities. In the present approach, probability refers to the subjective probabilities experts assign to certain events in the sense of their degree of belief, a concept that has been introduced in Section 2.2.1. It is very different from probability in the classical sense, which relates to the limiting frequency in a number of trials wich goes to infinity. No such 'trials' are possible in regard to an event that has not occurred yet, such as the composition of the German new vehicle fleet in 2030, or the average fuel consumption of new ICE in that year. Instead, the best available knowledge are the expectations of people who are very familiar with the subject, i.e., expert assessments. Thus, the aim underlying the elicitation of experts is to display their expectations for 2030, not in order to derive a prediction, but to gather the knowledge held by informed people in an expert-based approach, as discussed in Section 2.5. In this sense, the present approach is an attempt of stakeholder-based science.

In this section, I explain the choice of experts and sketch the elicitation procedure. Then, the largest part of the section deals with the presentation of elicitation results. In further paragraphs, an evaluation of the BBN by the experts is given, some patches are described which have been added after elicitation in order to fix remaining problems with the BBN, and finally, conclusions on the elicitation experience and outcomes are drawn.

4.4.1 The Choice of Experts

As the assessment of possible technology pathways until 2030 is at the heart of the present investigation, the choice of experts followed the aim of interviewing one high-ranked R&D expert from each OEM producing cars in Germany. This includes the companies Audi, BMW, Daimler, Ford Europe, Opel/GM Europe, Porsche, and Volkswagen. Although not producing cars in Germany, I added Toyota because of their special and possibly deviant position in regard to hybridization/electrification of cars and because they have a major representation in Germany[9].

Where possible, I directly contacted the research branches or specialized research centers of the respective OEM. I won four R&D experts for an interview. In two more cases, I was referred to top-level environmental officers. In one case, I talked to a technology communication officer. Unfortunately, one of the OEM contacted was unwilling to participate[10] and one declared to be unable to respond to my elicitation request within two months. The names and positions of experts can not be disclosed, as most experts preferred anonymity.

[9]The headquarters of Toyota Germany at Cologne have roughly 1500 employees, working on the company's formula 1 development and providing financial services, among others.

[10]The expert in question said that in regard to 2030 CO_2 emissions, due to a number of factors the development of which could not be assessed, there was too much uncertainty for making statements today. Some of the power of the BBN approach lies in the possibility to ask experts for conditional statements, and thus to refer some of the uncertainty on impact factors to those conditions. Unfortunately, I did not get the chance to have the method tried and evaluated by this expert.

In sum, I have elicited seven experts from six different OEM. Obviously, this set of experts does not meet the criteria of representativeness. However, the somewhat ad-hoc choice of experts is justified by two reasons: First, it is not intended to infer, e.g., the perspective of whole companies (whatever that may be), or of all R&D departments of OEM, or of all chief environmental officers of German OEM. Elicitation results as presented in the following will have to be taken to stand for themselves, namely as the revealed assessments of seven German experts working in the field and knowing a lot about what is going on today and what is in the focus of research and development. They also have to be taken as the positions of experts whose positions may involve quite a bit of company-strategic bias. Second, it has to be kept in mind that the present approach is innovative in that it combines subjective assessments with the toolkit of BBN. Testing what can be done with this approach and what are possible shortcomings and aspects to improve on does not call for a large number of BBN, but rather for a first trial with a manageable sample size. This is all the more important as the question of how to aggregate the individual BBN created for the different experts has not been solved in a satisfactory way, and even the task of displaying the results from different BBN together is complicated.

4.4.2 The Elicitation Procedure

The standard interview procedure according to the elicitation protocol is described in the following. The complete elicitation protocol used during the interviews can be found in the Appendix (see A.2). As all interviews were conducted in German language, it is available in German, only.

Compared to expert elicitation carried out in order to identify, rank and quantify impacts of climate related variables, many of which took a day of face-to-face interviewing (see, e.g., Morgan & Keith (1995), Morgan et al. (2001), Morgan et al. (2006), and Zickfeld et al. (2007)), the intensity of elicitation for quantifying the present BBN was rather small.[11] Due to expert availability, time and budget constraints, elicitation of conditional probability tables (CPT) was limited to roughly one hour per expert, during which experts were asked to specify conditional probabilities within the given BBN structure, which had been developed on the basis of a first round of semi-quantitative expert interviews (described in Chapter 3).

Experts were also asked to make changes to the structure where the given dependencies seemed unsatisfactory to them. As they were free to make changes

[11]For more details on elicitation methods, see Section 2.5.

to the proposed BBN, e.g., eliminate nodes or alter category boundaries, elicitation processes deviated more or less from what is described in the following.

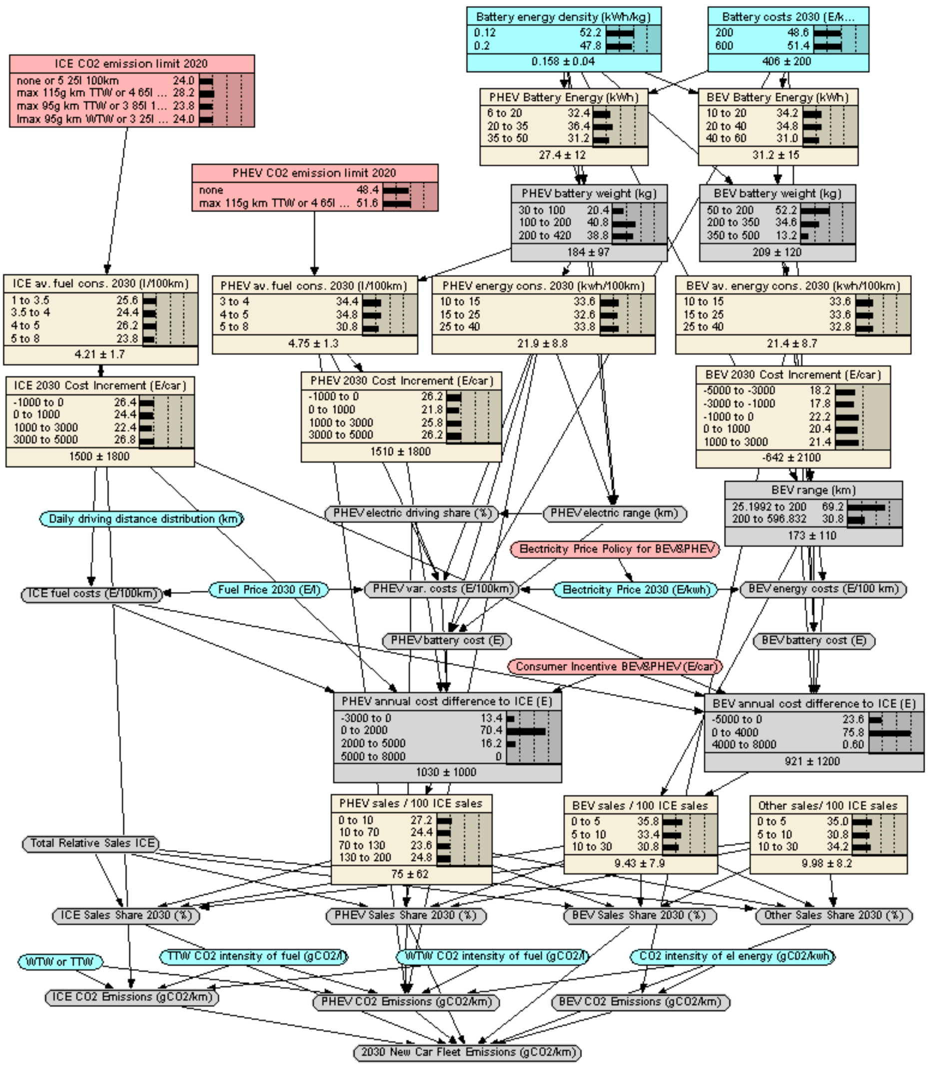


Figure 4.3: Graphic of the BBN in Hybrid Style

In each interview, initially, a short introduction to the research questions and the BBN approach was given and the expert was told what areas the questions would relate to.[12] Then, I pointed out what technologies are considered explicitly in the network and how they are distinguished. During the interview, a copy of the BBN as presented in Figure 4.3 was given to the expert for orientation. The figure shows the network in a 'hybrid' style: The beige nodes,

[12] In the sections regarding elicitation outcomes, wording will not be gendered as I did not interview any women in the second interview series.

CPT of which were asked from the experts (further called 'elicitation nodes'), as well as their parent nodes are displayed in belief-bar style. This means that their states are visible in Figure 4.3, with probabilities roughly uniformly distributed over all states in the elicitation nodes. All other nodes are condensed to labeled-box style in order to fit the whole image onto a single page, and in order not to distract attention.

The elicitation process consisted in going through the BBN node by node and asking the expert to fill in CPT for all elicitation nodes. Assigning probabilities to states of a dependent variable, given the state of some independent variable(s), is something I assumed the experts would be unfamiliar with. To simplify the task, I chose to start with a question common to them and first asked for the average fuel consumption of new ICE in 2030, given different states of regulation. For this variable, as for all following, I first specified the parent variable(s) and its (their) states. For ICE fuel consumption in 2030, the only parent variable is the (red) policy node 'ICE CO_2 emission limit 2020', which describes a policy of the European Union to bring down fuel consumption of combustion engine vehicles. Four possible states of the regulation variable were considered, which were deduced from the debate on a EU fuel consumption policy. The details have been described in Section 4.2.5. Vehicle fuel consumption is subdivided into four states (1 to 3.5, 3.5 to 4, 4 to 5 and 5 to 8 l/100km), which have been chosen such that there is a state which roughly fulfills each of the four regulation variants.

The associated CPT stored in the BBN is shown in Figure 4.4. On the left hand side, the four states of the independent variable (regulation) are listed rowwise. On the right hand side, the four states of the dependent variable (ICE fuel consumption) are given. For each given regulation, experts had to quantify their assessment of how probable it is that each of the consumption levels is met. They were asked to fill in the table line by line, assigning probabilities to each state of vehicle fuel consumption such that probabilities in each row (i.e., for each state of regulation) sum up to a full 100%. An example for probabilities entered by an expert can be seen in Figure 4.5.

ICE CO2 emission limit 2020	1 to 3.5	3.5 to 4	4 to 5	5 to 8
none or 5 25l 100km				
max 115g km TTW or 4 65l 100km				
max 95g km TTW or 3 85l 100km				
lmax 95g km WTW or 3 25l 100km				

Figure 4.4: An Example CPT

ICE CO2 emission limit 2020	1 to 3.5	3.5 to 4	4 to 5	5 to 8
none or 5 25l 100km	0	0	20	80
max 115g km TTW or 4 65l 100km	0	0	100	0
max 95g km TTW or 3 85l 100km	0	80	20	0
lmax 95g km WTW or 3 25l 100km	40	60	0	0

Figure 4.5: Filling in a CPT

A similar procedure was gone through for all elicitation nodes in the BBN. All variables relate to 2030 values. To increase readability, references to the year 2030 are left out in the following description.

One by one, experts were asked to specify **fuel and energy consumption** of the different vehicle types (nodes in the second row of beige nodes in Figure 4.3), more precisely

- ICE fuel consumption, given regulation
- PHEV fuel consumption, given regulation and PHEV battery weight
- PHEV electric energy consumption, given PHEV battery weight, and
- BEV electric energy consumption, given BEV battery weight.

Next, **battery parameters** for PHEV and BEV were elicited (nodes in the first row of beige nodes in Figure 4.3), namely

- PHEV battery energy, given battery costs and battery energy density, and
- BEV battery energy, given battery costs and battery energy density.

Then, **incremental costs** of the 2030 vehicle types as compared to today's ICE were asked for (nodes in the third row of beige nodes in Figure 4.3). This includes

- ICE incremental costs, given ICE average fuel consumption
- PHEV incremental costs, given PHEV average fuel consumption, and
- BEV incremental costs (unconditional).

Finally, **sales shares** relative to ICE sales were treated (nodes in the fourth row of beige nodes in Figure 4.3), i.e.,

- PHEV sales relative to ICE, given the annual cost difference of PHEV compared to ICE

- BEV sales relative to ICE, given the annual cost difference of BEV compared to ICE, and given BEV range, and
- Other vehicles sales relative to ICE (unconditional).

In the beginning of each interview, a hardcopy of the elicitation protocol was handed out to the experts, and they were asked to fill in the CPT by pencil. In parallel, I entered the values into the BBN on a laptop. In most cases, networks could be adapted to the expert's requirements and completed during the interview. I then compiled the network and showed it to the expert in order to give an idea of what could be done with a completed network and to check back whether the expert was content with the results the BBN produced. Due to time constraints, however, only rudimentary checks could be accomplished with most experts.

At the end of each interview, I asked the expert for an evaluation of the present BBN and the method in general. Last, it was discussed whether elicitation results should be anonymized.

4.4.3 Elicitation Results

In this section, the results from expert elicitation are presented. This is done node by node in the order of elicitation as described in the previous section. As experts' statements are of interest as such, they will be presented in a detailed way. For each node, probability tables are presented for each expert individually, and then depicted in a graphic for all experts together. The charts display the probabilities experts assigned to the states of a variable as bubbles, sizes of which correspond to the conditional probability assigned to a state. They will therefore be called 'bubble charts'. For each expert, a different bubble color is used, and experts which have not given an assessment for a specific variable have been put in brackets in the legends.

In order to allow tracing back what statements come from the same expert, experts have been numbered and the same number (as well as the same color in the bubble charts) always refers to the same expert in the following presentation. The numbers are not meant to introduce any kind of ranking.

By filling in probability tables, each of the seven experts has more or less completely specified an individual BBN. The resulting set of BBN will be analyzed in more detail in Section 4.5. In some cases, experts questioned the method or the network structure and were unwilling to provide CPT for a number of nodes. Moreover, some experts eliminated some nodes they deemed irrelevant. Such changes to the basic BBN structure as well as elicitation gaps will be documented in this section.

Expert 1:

1 to 3.5	3.5 to 4
20	80

Expert 2:

ICE CO2 emission limit 2020	1 to 3.5	3.5 to 4	4 to 5	5 to 8
none or 5 25l 100km	0	0	20	80
max 115g km TTW or 4 65l 100km	0	0	100	0
max 95g km TTW or 3 85l 100km	0	80	20	0
lmax 95g km WTW or 3 25l 100km	40	60	0	0

Expert 3:

ICE CO2 emission limit 2020	1 to 3.5	3.5 to 4	4 to 5	5 to 8
none or 5 25l 100km	0	0	75	25
max 115g km TTW or 4 65l 100km	0	80	20	0
max 95g km TTW or 3 85l 100km	10	90	0	0
lmax 95g km WTW or 3 25l 100km	30	70	0	0

Expert 4:

3.5 to 4	4 to 5
97	3

Expert 5:

ICE CO2 emission limit 2020	3.5 to 4	4 to 5	5 to 8
max 105g km TTW	0	95	5
max 95g km TTW	85	15	0

Expert 6:

ICE CO2 emission limit 2020	1 to 3.5	3.5 to 4	4 to 5	5 to 8
none or 5 25l 100km	0	0	100	0
max 115g km TTW or 4 65l 100km	0	0	100	0
max 95g km TTW or 3 85l 100km	0	100	0	0
lmax 95g km WTW or 3 25l 100km	70	30	0	0

Figure 4.6: Experts' CPT for 2030 ICE Fuel Consumption (l/100km)

4.4.3.1 ICE Fuel Consumption

Experts were asked to specify the probabilities that different levels of ICE average fuel consumption will be reached in 2030, provided that the European Union issues a specified regulation of vehicle fuel consumption by 2020. Regulation scenarios considered are as follows:[13]

1. No tightening of regulation beyond the limit that has been decided for 2012. The regulation already in place limits vehicle-side CO_2 emissions to 130 g/km, which translates to a fuel consumption of roughly 5.25 l/100km on the basis of today's fuel mix.

2. A fuel consumption limit of 115 gCO_2/km tank-to-wheel. This is roughly equivalent to 4.65 l of today's fuel mix per 100 km.

3. A limit of 95 gCO_2/km tank-to-wheel, i.e., about 3.95 l/100km.

4. 95 gCO_2/km as a well-to-wheel emission limit, which comes down to 3.25 l/100km.

Experts were asked to assign probabilities to different levels of vehicle fuel consumption in 2030 under each of the regulation scenarios. By fuel, I refer

[13]For the details of regulation scenarios, as well as on other inputs to the BBN, see Section 4.2.

to an average of liquid fuels, i.e., gasoline, diesel, and biofuels of both types. Four fuel consumption categories were proposed in the basic BBN, namely 1 to 3.5, 3.5 to 4, 4 to 5 and 5 to 8 l/100km. None of the experts made changes to these categories, but some thought that only two or three of them had positive probabilities. The CPT filled in by experts 1 throughout 6 are shown in Figure 4.6, and probability distributions are displayed in a bubble chart in Figure 4.7. Expert 7 did not fill in the CPT.

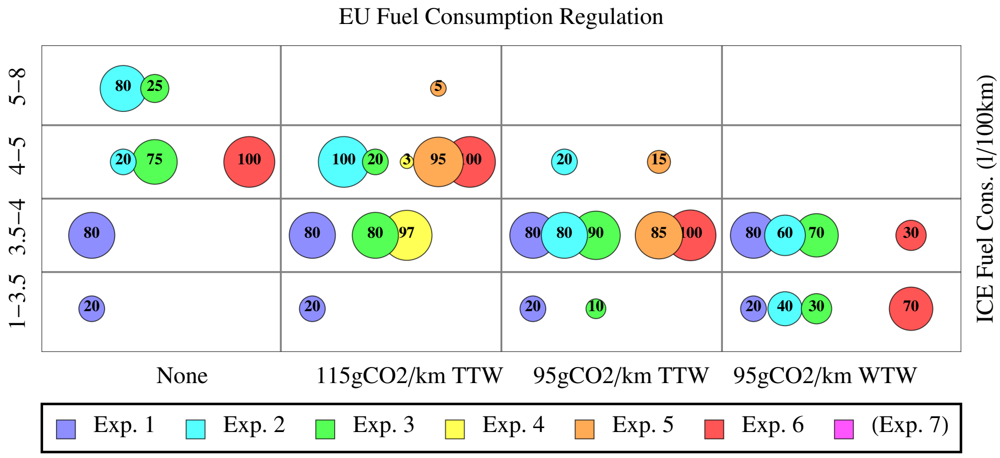


Figure 4.7: Bubblegraph for ICE Fuel Consumption

In Figure 4.7, regulation as the independent variable is sketched on the abscissa, with strictness of regulation scenarios increasing from left to right. Average ICE vehicle fuel consumption in 2030, the dependent variable, is put on the ordinate, with fuel consumption increasing from bottom to top. Probabilities assigned by the experts are illustrated by colored bubbles (one color is allocated to each expert), the area of which represents the probability an expert assigns to the respective state of fuel consumption, given the state of regulation. The numbers printed in the bubbles give the percentage value of probabilities.

As can be seen, probability weights are not equally distributed over all panels, but there is some concentration of weight in the panels on and around the diagonal top-left to bottom-right. This shows that most experts think that increasingly stringent EU fuel consumption regulation tends to bring down fuel consumption to some extent. This is true for experts 2, 3, 5, and 6.

In contrast, expert 1 has assigned the same weights to fuel consumption categories, regardless of regulation. This can also be seen from Figure 4.6, where probabilities of reaching fuel consumption levels have been assigned unconditionally by expert 1. He argued that 2030 German vehicle fuel consumption does not depend on European regulation, but will be determined through global competition which will foster a cut in consumption. He pointed out that his 20% chance of seeing a very low average consumption of 1 to 3.5 l/100km was related to the possible establishment of new mobility concepts, e.g., the widespread use of small city cars.

Expert 4 said that the EU had already settled a 95 gCO_2/km emission limit from 2020 on, which would result in a limit of 105 gCO_2/km on the vehicle side. He argued that in 2030, the German new car fleet would still consist of larger and more fuel consuming cars than the average European car. Thus, in their struggle to meet emission standards, OEM would redistribute emissions from their overall European fleets, allowing for slightly more emitting cars in Germany than in other European countries. For the German car fleet, he thought of 6 to 7% of emissions on top of the European limit of 105 g to be reached by the vehicles, and he based his assessment on this scenario. This amounts to allowed tank-to-wheel emissions of 111 to 112 gCO_2/km. In Figure 4.7, his probability bubbles are placed in the regulation category of 115 gCO_2 TTW, as this offers the best approximation.

Expert 5 explained that 100 g was a realistic assumption for a car-side CO_2 emission limit. He considered two scenarios, namely 95 and 105 gCO_2/km, pointing out that 95 g was the technical limit for emissions achievable by vehicles of today's average size. This assessment can not be displayed correctly in Figure 4.7. His assessment in case of a 105 g regulation has been included in the 115 g category, which comes closest to the expert's statement.

Expert 2 considered a regulation between the 95 and 115 gCO_2/km TTW categories to be realistic, but also gave his assessments of fuel consumption in case other regulation scenarios were realized.

Two experts (experts 3 and 5) made clear that the way fuel consumption and emissions were measured was very important. They said that they would base their assessments on the New European Driving Cycle (NEDC). I assume that all experts related their assessments to NEDC figures, as this is the current standard way of emission measurement and declaration.

Two experts discussed the decision to model fuel consumption explicitly dependent on regulation, only. Expert 3 pointed out that many factors, e.g., fuel prices, would drive fuel consumption, but was ready to assign probabilities within the proposed framework.

Expert 7, in contrast, said this was impossible. 2030 vehicle fuel consumption would depend on fuel prices, the development of standards of living and income distribution, to name just a few. Statements as asked for in the interview would imply many assumptions which would not be made explicit, and would presuppose a future development which could not be foreseen today. For the same reason, expert 7 was not ready to give probability distributions for most of the variables modeled in the BBN, such that there will be no statements by this expert in many of the following sections.

4.4.3.2 PHEV Fuel Consumption

Next, probability distributions for 2030 fuel consumption of plug-in hybrid electric vehicles were elicited. This variable describes fuel consumption when PHEV travel in combustion engine mode, i.e., running on energy from liquid fuels exclusively and not using additional electric energy from external sources stored in their battery. Energy originating from burning fuel but then recuperated and stored in the battery (in the sense of full or mild hybrid electric vehicles) may be used in this mode.

Fuel consumption of PHEV is modeled to depend on two parent variables, namely regulation and the weight of the battery on board. First, it is assumed that the EU regulation on ICE CO_2 emissions sketched in the previous section (Section 4.4.3.1) may be extended to encompass PHEV in combustion engine mode, as well. In fact, such an extension might be useful to avoid arbitrage by OEM, which might otherwise add a minimal PHEV component to ICE in order to circumvent regulation. For the present purposes, it is assumed that regulation will be less stringent for PHEV than for ICE, and that it applies to PHEV with an electric range of at least 30 km (PHEV-30). Thus, PHEV with smaller electric ranges would have to comply with the regulation for ICE. Two states of regulation for PHEV-30 are considered, namely:

1. There is no regulation on PHEV CO_2 emissions.
2. A PHEV emission limit of 115 gCO_2/km tank-to-wheel applies (this corresponds to roughly 4.65 l of today's fuel mix per 100 km).

As a second parent variable, the weight of batteries is considered influential for PHEV fuel consumption. The following three categories of battery weight are proposed:

1. 30 to 100 kg
2. 100 to 200 kg
3. 200 to 420 kg

For the node 'PHEV average fuel consumption 2030', three states are taken into consideration, namely 3 to 4, 4 to 5, and 5 to 8 l/100km. Because of the

Expert 2:

PHEV CO2 emission limit 2020	PHEV battery weight (kg)	3 to 4	4 to 5	5 to 8
none	30 to 60	60	40	0
none	60 to 100	80	20	0
ICE max 115g km TTW plus AddOn	30 to 60	80	20	0
ICE max 115g km TTW plus AddOn	60 to 100	100	0	0

Expert 3:

PHEV CO2 emission limit 2020	PHEV battery weight (kg)	3 to 4	4 to 5	5 to 8
none	30 to 100	90	10	0
none	100 to 200	20	70	10
none	200 to 420	0	0	100
max 115g km TTW or 4 65l 100km	30 to 100	30	70	0
max 115g km TTW or 4 65l 100km	100 to 200	20	80	0
max 115g km TTW or 4 65l 100km	200 to 420			

Expert 5:

6 l/100km

Expert 6:

PHEV CO2 emission limit 2020	PHEV battery weight (kg)	1 to 3.5	3.5 to 4	4 to 5	5 to 8
max 115g km TTW or 4 65l 100km	100 to 200	0	0	70	30
max 115g km TTW or 4 65l 100km	200 to 420	0	0	30	70
max 95g km TTW or 3 85l 100km	100 to 200	0	70	30	0
max 95g km TTW or 3 85l 100km	200 to 420	0	30	70	0
lmax 95g km WTW or 3 25l 100km	100 to 200	0	70	30	0
lmax 95g km WTW or 3 25l 100km	200 to 420	0	30	70	0

Figure 4.8: Experts' CPT for 2030 PHEV Fuel Consumption (l/100km)

extra weight caused by the two propulsion systems installed in PHEV, a lower fuel consumption (like the category 1 to 3.5 l/100km proposed for ICE) has not been suggested. The original CPT presented to the experts has the same categories as the one filled in by expert 3 (see Figure 4.8).

Only four out of seven experts elicited have given assessments for 2030 PHEV fuel consumption, which are shown in Figure 4.8. Of those who did not, expert 7 refused assigning probabilities for the reasons detailed in the previous section (Section 4.4.3.1). Experts 1 and 4 eliminated PHEV from the entire BBN. Expert 1 said that due to the inefficiency caused by carrying two propulsion systems, PHEV were a transitory technology that would not be sold any longer in 2030. By then, pure BEV would be available, especially for cities; otherwise pure ICE would be used. Expert 4 doubted that PHEV would reach an important market share at any point in time. He said their share would be clearly below 5% and thus deleted the category from the BBN as irrelevant.

The assessments given by four experts are depicted in Figure 4.9. The input variables have been put on the x/y-plane. Regulation is placed on the x-axis, with four increasingly strict states sorted from left to right. In addition to the two regulation categories originally included in the BBN model, expert 6 decided to consider two more categories, namely limits of 95 gCO_2/km TTW, and

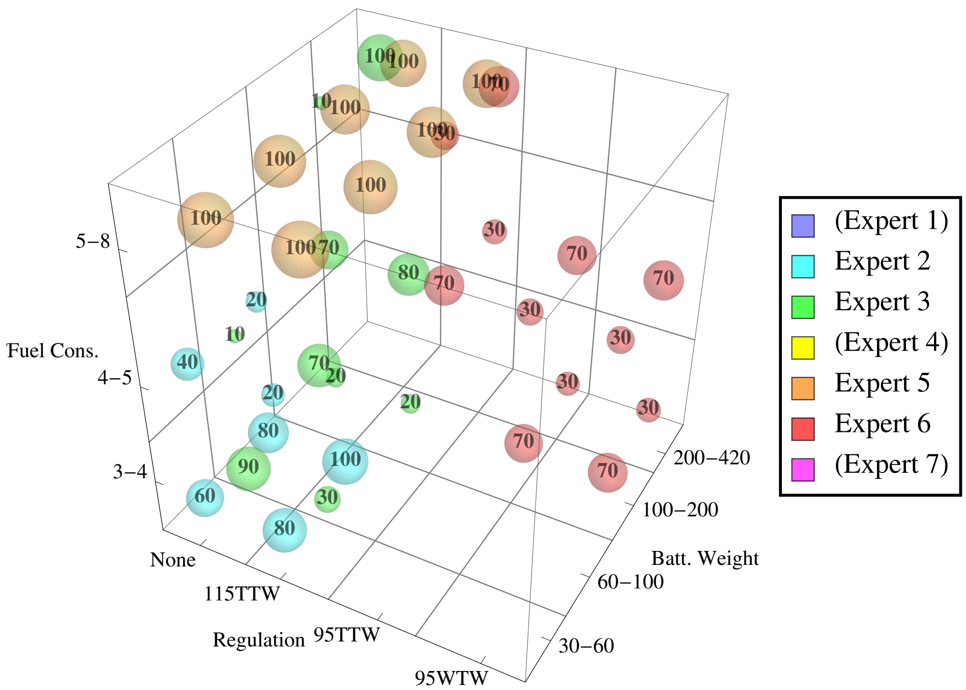


Figure 4.9: Bubblegraph for PHEV Fuel Consumption
x-axis: Regulation (emission limit in gCO_2/km), **y-axis:** Battery weight for 2030 PHEV (kg), **z-axis:** Fuel consumption of PHEV in combustion engine mode(l/100km).

95 gCO_2/km WTW, in order to have the same categories as for ICE regulation. These extra states have been included in the figure. As no other expert has considered these states of regulation, the respective panels of the figure remain empty apart from expert 6's assessment.

Battery weight is shown on the y-axis. Deviant from the three categories proposed to the experts, four categories have been used in the Figure, namely 30 to 60, 60 to 100, 100 to 200, and 200 to 420 kg. This has been done for allowing to represent the assessment of expert 2, who has subdivided the original category of 30 to 100 kg into two groups. The assessments of the experts who have used the original category 30 to 100 kg have been put onto the line between the first two categories. The dependent variable, PHEV fuel consumption, is placed on the z-axis with its three original categories, increasing from bottom to top.

Each expert could assign bubbles of 100 percent altogether for every combination of regulation and battery weight, that is, for every panel of the x/y-plane in Figure 4.9. As can be seen, expert 5 has assigned 100 percent of probability to a high PHEV fuel consumption of 6 l/100km, no matter what regulation and battery weight. He said that both variables did not have an important impact on PHEV fuel consumption.

Expert 2 considered PHEV battery weights of up to 100 kg, only. In regard to regulation, he pointed out that he expected PHEV fuel consumption to be coupled to ICE regulation, with an add-on allowed for PHEV. These add-ons could depend on the weight of the PHEV battery, e.g., there could be an extra 30% of emissions allowed for vehicles carrying up to 60 kg of batteries, and 60% for up to 100 kg of batteries. This expert imagined PHEV as rather small vehicles; he explained that batteries heavier than 100 kg would only be used in the rare case that a large vehicle would be equipped as PHEV.

Expert 3 did not change the battery weight categories or regulation scenarios proposed. However, he said that 400 kg of batteries would be a challenge regarding weight, vehicle construction, and charging times. In case a regulation on PHEV fuel consumption would be put in place, he contested that PHEV would be equipped with a very large battery, and thus he did not fill in the last line of the CPT (see Figure 4.8).

Expert 6 was sure that by 2030, there will be an emission limit for PHEV. Thus, he eliminated the regulation state ‘none’. Instead, he added the same regulation scenarios as used for ICE, and altered the fuel consumption categories such that the same boundaries apply as for ICE. As he always gave zero probability to the lowest category of 1 to 3.5 l/100km, his assessments can roughly be compared to those of other experts, except that the lower boundary of the lowest category used is 3.5 (instead of 3) l/100km in his case. In contrast to expert 2, he did not expect any PHEV with less than 100 kg of batteries to be built.

For the three experts who specified conditional probabilies (experts 2, 3 and 6), both parent variables play a role. A CO_2 emission limit moves probabilities towards lower fuel consumption, and increased battery weight augments probabilities of higher fuel consumption. Therefore, the probability bubbles of these experts tend to shift weight towards lower consumption (i.e., from top to bottom) for stricter regulation (from left to right) and smaller battery weight (from back to front). However, as different experts adapted the category scheme in individual ways, it is difficult to compare their assessments.

4.4.3.3 PHEV Electric Energy Consumption

Apart from the combustion engine mode just discussed, PHEV can also operate in electric mode. For technical reasons, it is assumed that in this mode, they use electric energy from external sources only. In practice, such a clear-cut distinction will not always be possible, as the battery may contain recuperated energy originating from fuel, and as, depending on the PHEV system, some of

Expert 2:

PHEV battery weight (kg)	10 to 15	15 to 25	25 to 40
30 to 60	20	80	0
60 to 100	40	60	0

Expert 3:

PHEV battery weight (kg)	10 to 15	15 to 25	25 to 40
30 to 100	0	80	20
100 to 200	0	60	40
200 to 420	0	10	90

Expert 5:
18 kWh/100km

Expert 6:

PHEV battery weight (kg)	10 to 15	15 to 25	25 to 40
100 to 200	0	50	50
200 to 420	0	70	30

Expert 7:
(20 to 40 kWh/100km)

Figure 4.10: Experts' CPT for 2030 PHEV Electric Energy Consumption (kWh/100km)

them may be designed for using both propulsion systems even if the battery is fully charged. For the present BBN, however, it is assumed that PHEV first consume the energy charged into their battery from plug, and only make use of their ICE system when the battery is nearly empty, in the sense of a range extender. Experts have been asked to imagine such a kind of vehicle and to give an assessment of electric energy consumption of PHEV in charge-depleting mode.

As for PHEV fuel consumption discussed in the previous section (Section 4.4.3.2), it was assumed that PHEV energy consumption depends on the weight of the battery it carries. However, no regulation for PHEV CO_2 emissions in electric mode is considered, leaving battery weight as the only independent variable, for which the same three categories were considered as before, i.e., 30 to 100, 100 to 200, and 200 to 420 kg.

Experts were asked to assign conditional probabilities to three states of PHEV energy consumption, i.e., 10 to 15, 15 to 25, and 25 to 40 kWh/100km. As experts 1 and 4 had eliminated PHEV from their BBN, they gave no assessments for the present node. Again, expert 7 did not fill in the CPT. However, his assessment of PHEV energy consumption could be deduced from statements he made at a later stage of the interview. He said if battery costs dropped considerably by 2030, PHEV battery energy should be 10 to 20 kWh when batteries are fully charged (see Section 4.4.3.5), and their electric range should be roughly 50 km. PHEV electric energy consumption results as 20 to 40 kWh/100km, but as the expert did not make this statement explicitly, it has been put in brackets in Figure 4.10, and has not been included in the bubble chart in Figure 4.11.

Four experts gave their assessments explicitly, diverging strongly in their opinions on the role of PHEV. Expert 2 narrowed down the range of PHEV battery weight to a maximum of 100 kg and sticked to his subdivision of the originally smallest category of 30 to 100 kg into two categories of 30 to 60 and 60 to 100 kg. He depicted PHEV as relatively small, moderately motorized cars. In contrast, expert 6 eliminated the lowest battery weight category, assuming that PHEV would be rather large cars and carry at least 100 kg of batteries. Experts 2 and 6 both assumed that PHEV energy consumption was likely to decrease with increasing battery weight.

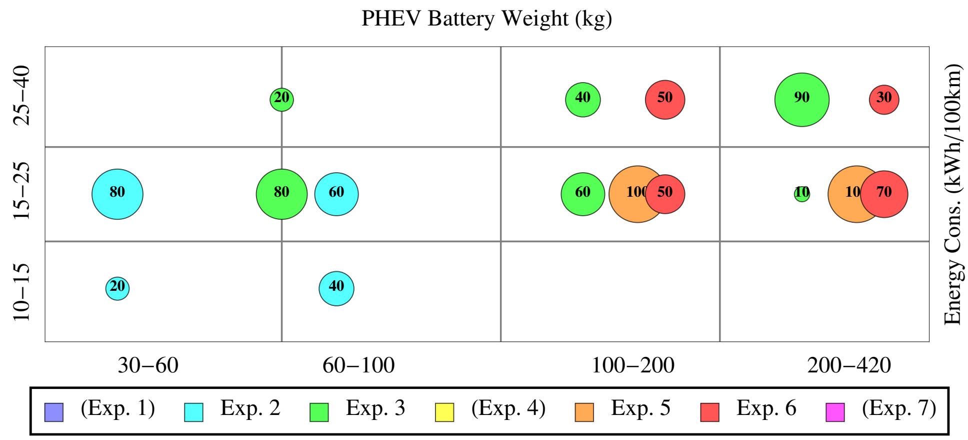


Figure 4.11: Bubblegraph for PHEV Electricity Consumption

Expert 3 considered the battery weight categories proposed and expected PHEV energy consumption to increase with a heavier battery. In Figure 4.11, the lowest battery energy category has been subdivided as proposed by expert 2 in order to be able to show his assessment, and the conditional probabilities for the original category of 30 to 100 kg of battery weight given by expert 3 have been placed on the line dividing the two subcategories.

As before, expert 5 gave an unconditional PHEV energy consumption of 18 kWh/100km. This has been added to the bubble graph as 100 per cent of probability for the category of 15 to 25 kWh/100km for the two highest battery weight categories, as the lower battery weight categories are incompatible with the expert's judgement of battery energy installed which will be described later (see Section 4.4.3.5). He said he imagined 2030 PHEV as long-distance vehicles with a range of roughly 800 km in ICE mode plus 100 to 200 km in electric mode.

For PHEV, it is evident that experts' judgements of their characteristics and role diverge strongly. Two experts think that they will not play any role in the 2030 German new car fleet (experts 1 and 4). Two experts imagine PHEV as large, heavy cars designed for long-distance driving with up to 200 km of electric range and a full-fledged combustion engine (experts 5 and 6). One expert (expert 2) thinks that PHEV will be rather small, light vehicles with downsized ICE. Finally, two experts did not describe a clear picture of the role of 2030 PHEV, but agreed that 2030 PHEV should have an electric range of 50 km (experts 3 and 7).

4.4.3.4 BEV Electric Energy Consumption

The next variable experts were asked to specify conditional probabilities for is electric energy consumption of BEV sold in Germany in 2030. BEV energy consumption was modeled in the BBN to depend on the weight of the batteries it carries. As BEV operate only in electric mode, larger batteries were proposed than for PHEV. The following three categories of BEV battery weight were considered:

- 50 to 200 kg
- 200 to 350 kg
- 350 to 500 kg

As propulsion of BEV is similar to propulsion of PHEV in purely electric mode, for BEV, the same energy consumption levels were implemented as for PHEV, namely 10 to 15, 15 to 25, and 25 to 40 kWh/100km.

CPT specified by the experts are listed in Figure 4.12. Two experts (experts 1 and 7) did not fill in the CPT. Expert 1 thought the question of BEV energy consumption was not well framed. He expected BEV energy consumption to depend on battery development and said that 2030 BEV would be built such that they could travel 100 km on one charge of 100 kg of the batteries available by then. The weaker the batteries, the smaller and lighter BEV would have to be.

For expert 7, a range of BEV energy consumption could again be calculated from the battery energy he specified later to be 50 to 100 kWh (see Section 4.4.3.6), and his statement that BEV would need to travel 300 to 400 km on one charge in order to be marketable. From these figures, a BEV energy

Expert 2:

BEV battery weight (kg)	10 to 15	15 to 25	25 to 40
50 to 200	100	0	0
200 to 350	40	60	0
350 to 500	0	20	80

Expert 3:

BEV battery weight (kg)	10 to 15	15 to 25	25 to 40
50 to 200	10	60	30
200 to 350	0	50	50
350 to 500	0	0	100

Expert 4:

BEV battery weight (kg)	10 to 15	15 to 25	25 to 40
50 to 200	80	20	0

Expert 5:
10 kWh/100km

Expert 6:

BEV battery weight (kg)	10 to 15	15 to 25	25 to 40
200 to 350	0	50	50
350 to 500	0	70	30

Expert 7:
(12.5 to 33.3 kWh/100km)

Figure 4.12: Experts' CPT for 2030 BEV Electricity Consumption (kWh/100km)

consumption of 12.5 to 33.3 kWh/100 km can be deduced, given in brackets in Figure 4.12.

The conditional probabilities given by experts 2 throughout 6 are displayed in the bubble chart in Figure 4.13. It can be seen that for experts 2 and 3, there is a tendency of probabilities to shift towards higher BEV electricity consumption with increasing battery weight. Both experts take the whole range of battery weights and energy consumption proposed into consideration. Both think that BEV are more attractive if they can travel larger ranges, and expert 2 sees a BEV range of at least 100 km as a minimum requirement.

Experts 4 and 5 think of BEV as relatively small vehicles used within cities or for short-distance traveling. They both put high probability on a relatively low BEV energy consumption. Expert 4 added that unless a breakthrough in battery technology occurred before 2030, BEV ranges would be 150 km at most. He limited BEV battery weight to 200 kg. Expert 5 said that BEV would be designed to transport one or two persons only and specified their energy consumption as 10 kWh/100km, unconditionally. But as a battery of 200 kg and more is neither compatible with his imagination of BEV as small vehicles nor with his assessment of battery energy installed given later on (see

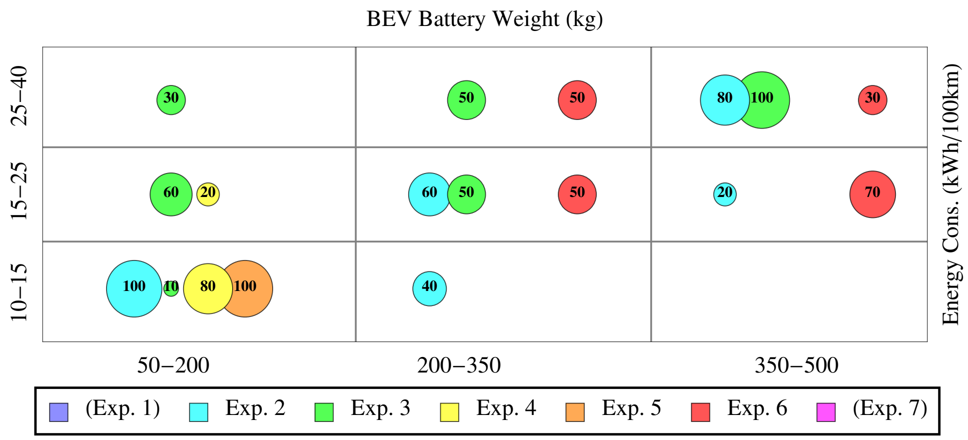


Figure 4.13: Bubblegraph for BEV Energy Consumption

Section 4.4.3.6), his assessment was interpreted to relate to the lowest battery weight category of 50 to 200 kg only, as displayed in Figure 4.13.

Expert 6 shared the image of BEV as smaller cars used for daily commuting, but assumed that they would have at least 200 kg of batteries on board. In his assessment, the probability of high BEV electricity consumption slightly decreased with higher battery weight.

4.4.3.5 PHEV Battery Energy

Once fuel and energy consumption had been specified, the next step in the interviews was to ask for the capacity of PHEV and BEV batteries, i.e., the amount of energy they can store when fully charged. For both PHEV and BEV, the BBN builds on the assumption that battery capacity depends on battery technology development in two regards, namely on the development of their costs and of their energy densities. Battery costs directly influence the choice of car batteries sizes by OEM. Battery energy density determines the weight batteries of a given capacity add to a vehicle which may be a prohibitive argument. For battery costs, two scenarios have been implemented in the BBN:

- 600 $€_{2008}$/kWh, and
- 200 $€_{2008}$/kWh.

In regard to battery energy density, two values are considered, as well, namely

- 0.12 kWh/kg, and
- 0.2 kWh/kg.

Expert 2:

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	6 to 10	10 to 15	15 to 20
200	0.12	60	30	10
200	0.2	50	40	10
600	0.12	85	10	5
600	0.2	80	15	5

Expert 3:

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	6 to 20	20 to 35	35 to 50
200	0.12	90	10	0
200	0.2	80	20	0
600	0.12	100	0	0
600	0.2	90	10	0

Expert 5:
35 kWh

Expert 6:

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	12 to 20	20 to 50
200	0.12	30	70
200	0.2	0	100

Expert 7:
10 to 20 kWh

Figure 4.14: Experts' CPT for 2030 PHEV Battery Energy (kWh)

An explanation for this choice of battery parameters has been given in Section 4.2.3. For the node of PHEV battery energy, three states were proposed to the experts: 6 to 20 kWh, 20 to 35 kWh, and 35 to 50 kWh.

As experts 1 and 4 had eliminated PHEV from their BBN, they did not specify PHEV battery energy. All other experts gave their assessments as shown in Figure 4.14. Most experts made changes to the categories proposed, and none of them used them all. Expert 6 was the only one to consider very high PHEV battery energy of up to 50 kWh. Expert 5 gave a value of 35 kWh, unconditionally. Not very astonishingly, these two experts imagine PHEV as relatively large, heavy cars with major electric range, as described before (see Section 4.4.3.3).

The other experts assigned positive probabilities to battery energy over the intervals of 6 to 35 kWh (expert 3, with higher probability on lower battery energy values), 6 to 20 kWh (expert 2), and 10 to 20 kWh (unconditionally, expert 7). These assessments correspond to images of PHEV either as smaller, lighter cars, or with minor electric ranges.

In Figure 4.15, expert assessments are displayed as probability bubbles. While on the x- and y-axes, the original categories for battery costs and battery energy density are used, z-axis categories for PHEV battery energy have been changed according to the experts' assessments. The lowest original category of

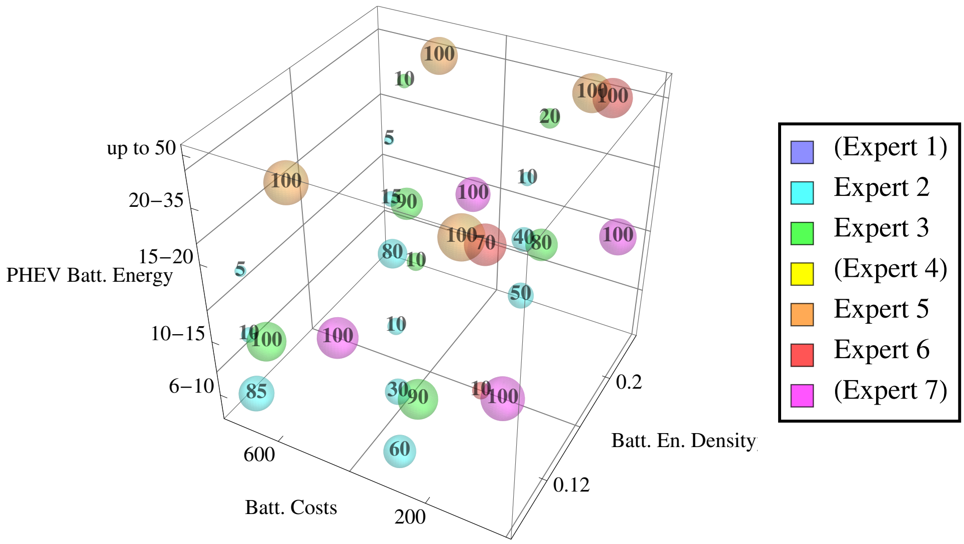


Figure 4.15: Bubblegraph for PHEV Battery Energy
x-axis: Battery Costs 2030 (Euro/kWh), **y-axis:** Battery Energy Density 2030 (kWh/kg), **z-axis:** PHEV Battery Energy 2030 (kWh).

6 to 20 kWh has been subdivided into three categories (6 to 10, 10 to 15, and 15 to 20 kWh) in order to represent the CPT of expert 2. Assessments of other experts referring to the lowest original category have been placed in the second of the three new categories (10 to 15 kWh). A fourth category corresponding to the original one of 20 to 35 kWh has been kept. Expert 5's 35 kWh has been put at the upper boundary of the fourth category. None of the experts has used the highest original category of 35 to 50 kWh. For expert 6's probabilities for 20 to 50 kWh, a fifth category of 'up to 50 kWh' has been introduced.

The figure gives a mixed impression of dependencies. On the x-axis, batteries get cheaper from left to right; on the y-axis, energy density increases from front to back. For experts 2, 3 and 6, probabilities of higher PHEV battery energy increase with more favorable battery development. For all three experts, probability weights move higher on the z-axis representing battery energy from front left to back right.

Expert 2 pointed out that PHEV battery energy was predominantly driven by battery costs. In his CPT, energy density has a minor impact. Expert 3 said that he found the way the question of battery energy was framed in the BBN unconvincing. He said that vehicle weight and user profiles would be more important for the battery energy needed than the parent variables implemented. Expert 6 eliminated the higher battery cost category of 600 €$_{2008}$/kWh which he found unrealistic, and said that he assigned a 70 % probability that a battery energy density of 0.2 kWh/kg would be reached by 2030.

In contrast to the three experts who made their assessments of 2030 PHEV battery energy conditional on at least one of the proposed variables, for experts 5 and 7, battery energy does not depend on battery costs or battery energy density. As none of them excluded any category of the battery development variables, their assessments have been added to all four fields of battery cost/energy density combinations in Figure 4.15. However, some combinations may not have been intended by the experts. For example, expert 7 said that the problem of battery weight could be handled, but battery costs would be critical for PHEV (and BEV) use. In the high battery cost case, i.e., costs of 600 €$_{2008}$/kWh, a 20 kWh battery, the highest battery energy considered by expert 7, would cost 12,000 €$_{2008}$. It is unlikely that expert 7 thinks PHEV could be sold if batteries alone came at such a prize. Expert 5 mentioned that he expected batteries to improve by 2030, but that he did not expect battery technology to make any spectacular jumps.

4.4.3.6 BEV Battery Energy

Next, BEV battery capacity assessments were elicited from the experts. The same independent variables were used as for PHEV battery energy – battery costs and battery energy density. Their states were defined in the same way again (see the previous Section 4.4.3.5). As BEV depend exclusively on electric energy from their battery, battery energy categories were originally set to allow for higher battery capacity than in the case of PHEV, with three categories of 10 to 20, 20 to 40, and 40 to 60 kWh.

The probability tables of the experts can be seen in Figure 4.16. Four experts have filled in the CPT, and two have given unconditional values. Expert 1 did not give an assessment because he felt uncomfortable with the way the question was framed.

Experts 2, 3 and 7, who think of BEV as covering large ranges or being vehicles of today's standard size (see Section 4.4.3.4), assigned high probabilities to relatively high BEV battery capacity values. Expert 7 even gave an unconditional assessment of 50 to 100 kWh, which is beyond the highest category proposed.

The experts who tend to think of BEV as smaller city vehicles narrowed down the range of BEV battery capacity more or less strongly. Expert 6 assigned a maximum of 50 kWh in case battery energy density develops well, less otherwise. Expert 4 eliminated the highest battery energy category of 40 to 60 kWh, arguing that BEV batteries of this size would be too expensive. He added that in the case of a battery price of 600 €$_{2008}$/kWh, the BEV mar-

Expert 2:

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	10 to 20	20 to 40	40 to 60
200	0.12	0	20	80
200	0.2	0	20	80
600	0.12	60	40	0
600	0.2	50	50	0

Expert 3:

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	10 to 20	20 to 40	40 to 60
200	0.12	0	40	60
200	0.2	0	10	90
600	0.12	10	80	10
600	0.2	0	80	20

Expert 4:

Battery costs 2030 (E/kWh)	10 to 20	20 to 40
200	90	10
600	100	0

Expert 5:
15 kWh

Expert 6:

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	24 to 40	40 to 50
200	0.12	100	0
200	0.2	0	100

Expert 7:
50 to 100 kWh

Figure 4.16: Experts' CPT for 2030 BEV Battery Energy (kWh)

ket would be extremely small, anyway. Expert 5 was sure that BEV battery capacity would not become very large and assigned an unconditional 15 kWh.

Of the two parent variables, battery cost had a more important impact on BEV battery energy for most experts (experts 2, 3, 4, and 7). Expert 6 excluded the higher battery cost scenario.

This can also be seen from the bubble chart in Figure 4.17, which summarizes the probability assessments of all experts. As experts have not made any changes to parent variable states, these are as originally implemented in the BBN. For the variable BEV battery energy, the original three states (10 to 20, 20 to 40, and 40 to 60 kWh) are plotted, as well, as they have been accepted by many experts. To allow for the higher assessment of expert 7 to be included, a fourth category has been introduced which is meant to roughly represent 50 to 100 kWh, although proportions have been narrowed down a bit, and the category overlaps with the original one of 40 to 60 kWh. Assessments of expert 6, who has made some changes to the category system, are placed close to the respective category boundaries.

As before, unconditional expert judgements have been included for all combinations of parent variable categories. As expert 5 did not exclude any battery cost or energy density category, his unconditional assessment of BEV battery

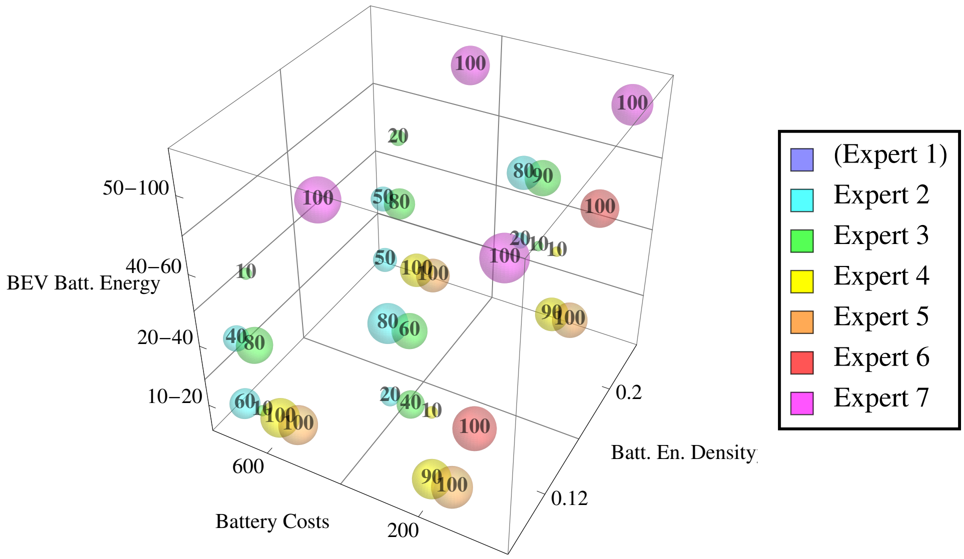


Figure 4.17: Bubblegraph for BEV Battery Energy
x-axis: Battery Costs 2030 (Euro/kWh), **y-axis:** Battery Energy Density 2030 (kWh/kg), **z-axis:** BEV Battery Energy 2030 (kWh).

capacity was displayed to hold for any combination of parent variable states. Expert 7 did not rule out any of the battery cost or energy density scenarios, either. However, as he assumed very high unconditional BEV battery energy of 50 to 100 kWh, both costs and weight will pose problems. Related battery costs alone are 10,000 to 20,000 €$_{2008}$ per car even under the favorable battery cost scenario, and 30,000 to 60,000 €$_{2008}$ under the unfavorable one. BEV battery weight is 250 to 500 kg or 417 to 833 kg in the two battery energy density scenarios. In none of the possible combinations, it seems realistic that BEV will be technically viable and marketable – battery development would need to be much better than assumed here. Still, expert 7's requirement for BEV battery capacity is included in the bubble graph for all four combinations of scenarios, as it would be arbitrary to leave some of them out.

Expert 4 has eliminated the dependency of BEV battery capacity on battery energy density, arguing that battery energy density and the related question of battery weight was of minor importance and battery volume was a more critical point. In Figure 4.17, this is treated as conditional independence of BEV battery energy from battery energy density.

4.4.3.7 ICE Incremental Costs

In a next step, experts were asked to give cost estimates for the three different vehicle types in 2030, starting with ICE. To simplify elicitation, only cost dif-

Expert 1:

ICE av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
1 to 3.5	0	0	50	50
3.5 to 4	0	70	30	0

Expert 2:

ICE av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
1 to 3.5	0	0	60	40
3.5 to 4	0	100	0	0
4 to 5	0	100	0	0
5 to 8	100	0	0	0

Expert 3:

ICE av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
1 to 3.5	0	0	0	100
3.5 to 4	0	0	10	90
4 to 5	0	5	80	15
5 to 8	0	30	70	0

Expert 4:

ICE av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
3.5 to 4	0	0	100	0
4 to 5	0	0	100	0

Expert 5:

ICE av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
3.5 to 4	0	100	0	0
4 to 5	0	0	100	0
5 to 8	0	0	0	100

Expert 6:

ICE av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
1 to 3.5	0	0	0	100
3.5 to 4	0	0	70	30
4 to 5	0	70	30	0
5 to 8	100	0	0	0

Expert 7:

ICE av. fuel cons. 2030 (l/100km)	0 to 1000	1000 to 3000	3000 to 5000	5000 to 8000
1 to 3.5	0	0	0	100
3.5 to 4	0	0	100	0
4 to 5	0	100	0	0
5 to 8	100	0	0	0

Figure 4.18: Experts' CPT for 2030 ICE Cost Increment (€$_{2008}$)

ferences compared to the cost of an average ICE vehicle in 2008 are required in the BBN, and experts did not need to specify absolute vehicle costs. In order not to have to deal with inflation, all costs were specified in real €$_{2008}$.

In this section, experts' assessments of the cost difference of a 2030 ICE compared to a 2008 ICE vehicle are presented. ICE incremental costs have been modeled in the BBN to depend on 2030 ICE average fuel consumption. For this parent variable, categories apply as introduced in Section 4.4.3.1: 1 to 3.5, 3.5 to 4, 4 to 5, and 5 to 8 l/100km. For ICE incremental costs, four categories were proposed to the experts, namely −1000 to 0, 0 to 1000, 1000 to 3000, and 3000 to 5000 €$_{2008}$.

As Figure 4.18 shows, all seven experts filled in the ICE cost increment table, and none of them changed the boundaries of the categories proposed. However, five experts assigned zero probability to the lowest cost category of −1000 to 0 €$_{2008}$, i.e., they did not think that by 2030, ICE could be cheaper than today under any circumstances. One expert (expert 7) added a high cost increment category of 5000 to 8000 €$_{2008}$, and expressed the opinion that ICE consuming only 1 to 3.5 l fuel per 100 km would belong to this category.

Expert 1 limited 2030 ICE fuel consumption to a maximum of 4 l/100km. For each state of ICE fuel consumption, he considered two categories for ICE incremental costs. He pointed out that the higher one would be realized, respectively, if air pollutant regulation stricter than Euro 6 had to be met by 2030. Expert 4 limited possible 2030 ICE fuel consumption states to the range of 3.5 to 5 l/100km and assigned a constant probability of 100 percent to incremental costs of 1000 to 3000 €$_{2008}$.

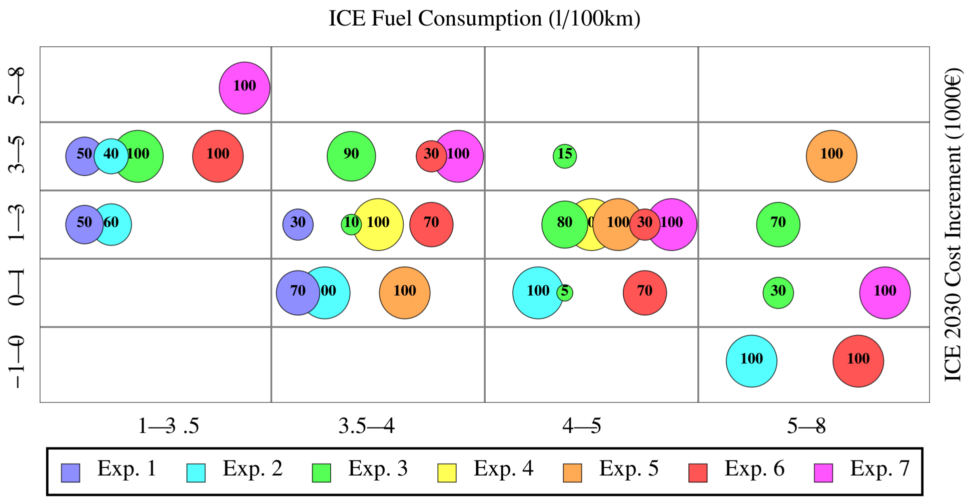


Figure 4.19: Bubblegraph for ICE Incremental Costs

The assessments of all experts are represented in a bubble chart in Figure 4.19. As can be seen, the bulk of probability mass is placed diagonally from top left to lower right. This indicates that experts think that there is a relationship between ICE fuel consumption and costs, and that most of them agree that a lower fuel consumption tends to drive incremental costs higher. Two experts disagree – expert 4 has fixed incremental costs at 1000 to 3000 €$_{2008}$, and expert 5 matches higher fuel consumption to higher vehicle costs.

Two experts (experts 3 and 7) discussed the aspect that the costs of reduced ICE fuel consumption depend on the way it is reached: If average car size is decreased, fuel consumption can be diminished at low, possibly negative costs; otherwise, expensive efficiency measures have to be taken. Both experts based their assessments for 2030 ICE incremental costs (as well as for other vehicle types' incremental costs) on the assumption that the 2030 new car fleet is composed of vehicles of the same average size as today. In contrast, the assessment of expert 5, who matches lower fuel consumption to lower costs, is possibly based on the assumption that lower 2030 ICE fuel consumption will be reached by building smaller cars, on average.

4.4.3.8 PHEV Incremental Costs

Next, experts were asked for their probability distributions on 2030 PHEV incremental costs compared to the costs of average 2008 ICE vehicles. For PHEV, the cost increment relates to all costs of the vehicle (including costs for the electric propulsion system) but does not include battery costs. In the BBN, battery costs are calculated from experts' specifications of PHEV battery capacity (elicited as described in Section 4.4.3.5) and battery development scenarios.

In analogy to ICE, in the BBN, PHEV incremental costs are modeled to depend on PHEV fuel consumption in combustion engine mode. For the parent variable PHEV fuel consumption, three states were suggested – 3 to 4, 4 to 5 and 5 to 8 l/100km. For PHEV incremental costs, the same four categories were proposed as for ICE incremental costs, namely −1000 to 0, 0 to 1000, 1000 to 3000, and 3000 to 5000 €$_{2008}$.

Figure 4.20 presents the CPT provided by five experts. The remaining two, experts 1 and 4, had eliminated PHEV from their BBN and did not provide tables. Experts 2 and 3 restricted their estimates of PHEV incremental costs to −1000 to 1000 €$_{2008}$. Expert 2 explained that PHEV would have smaller engines than ICE, which reduced their costs. Expert 5 considered a PHEV consuming roughly 6 l fuel per 100 km, and said this vehicle would cost 1000 to 3000 €$_{2008}$ on top of the price of a current average ICE vehicle. Expert 6

Expert 2:

PHEV av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
3 to 4	80	20	0	0
4 to 5	100	0	0	0
5 to 8	100	0	0	0

Expert 3:

PHEV av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
3 to 4	50	50	0	0
4 to 5	90	10	0	0
5 to 8	100	0	0	0

Expert 5:

PHEV av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
6	0	0	100	0

Expert 6:

PHEV av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
1 to 3.5	0	0	0	100
3.5 to 4	0	0	70	30
4 to 5	0	70	30	0
5 to 8	100	0	0	0

Expert 7:

PHEV av. fuel cons. 2030 (l/100km)	0 to 1000	1000 to 3000	3000 to 5000
3 to 4	0	0	100
4 to 5	0	100	0
5 to 8	50	50	0

Figure 4.20: Experts' CPT for 2030 PHEV Cost Increment (€$_{2008}$)

changed the fuel consumption categories in order to have the same categories as for ICE fuel consumption. As he assessed costs for the electric motor and drivetrain to be of minor importance, he used the same CPT values for PHEV incremental costs as for ICE incremental costs. Expert 7 eliminated the lowest

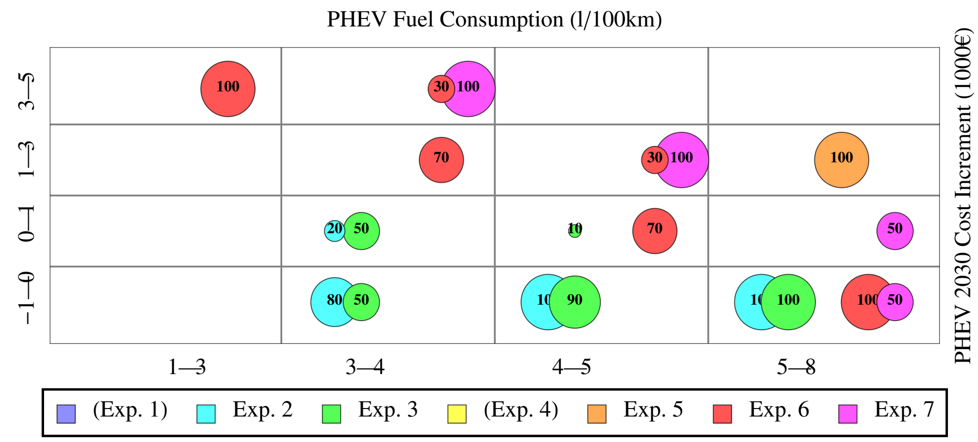


Figure 4.21: Bubblegraph for PHEV Incremental Costs

(negative) cost category.

Figure 4.21 shows the assessments as a bubble chart. The chart is less crowded than that for ICE incremental costs of Figure 4.19, but the tendency of experts to place probability mass diagonally from top left to bottom right persists. This shows that most experts believe that the connection of lower fuel consumption to higher costs holds for PHEV, as well. Comparing the two bubble charts, more experts are willing to give some probability to negative cost increments for PHEV than for ICE, and less experts assign weight to the highest original cost increment category of 3000 to 5000 €$_{2008}$. This can partly be explained by the fact that only one expert thinks 2030 PHEV might have a fuel consumption below 3 l/100km. Summing up, experts who imagine PHEV on the roads by 2030 think that they will tend to be more fuel consuming in internal combustion engine mode and less expensive than 2030 ICE.

4.4.3.9 BEV Incremental Costs

For 2030 BEV, experts were asked to specify their probability distributions of incremental costs compared to current ICE, as well. As for PHEV, BEV cost increments include all costs on the vehicle side, but exclude battery costs, which are modeled separately in the BBN.

For BEV, of course, there is no fuel consumption level to be met. In contrast to ICE and PHEV cost increments, BEV cost increments were thus included in the BBN as an 'orphan', a variable that does not depend on any parent nodes. Of course, as for other vehicle types, BEV costs depend strongly on the size and quality of the vehicles. However, the question of the configuration of future BEV – as small city vehicles or rather as vehicles of today's standard size and range – was not modeled explicitly in the BBN. Still, the image an expert has in his mind when thinking of BEV is very important for his cost assessment. As far as experts have revealed these images, they have been documented in Section 4.4.3.4. Roughly, experts 1, 4, 5 and 6 think of BEV as smaller vehicles with rather limited ranges used within cities, while experts 2, 3 and 7 think that BEV need to offer larger ranges to be attractive.

Five states of BEV cost increments were originally implemented in the BBN: −5000 to −3000, −3000 to −1000, −1000 to 0, 0 to 1000, and 1000 to 3000 €$_{2008}$. Compared to the states proposed for 2030 ICE and PHEV cost increments, states for BEV cost increments are shifted to the negative side. This has been done because BEV may become cheaper than current standard ICE vehicles both because they do not need a combustion engine and the associated transmission system, and because they might be conceived as smaller vehicles.

Expert 1:

-5000 to -3000	-3000 to -1000	-1000 to 0	0 to 1000	1000 to 3000
0	0	0	0	100

Expert 2:

-5000 to -3000	-3000 to -1000	-1000 to 0	0 to 1000	1000 to 3000
0	10	80	10	0

Expert 3:

-5000 to -3000	-3000 to -1000	-1000 to 0	0 to 1000	1000 to 3000
30	50	20	0	0

Expert 4:

-5000 to -3000	-3000 to -1000	-1000 to 0	0 to 1000	1000 to 3000
0	90	10	0	0

Expert 5:

-5000 to -3000	-3000 to -1000	-1000 to 0	0 to 1000	1000 to 3000
0	0	100	0	0

Expert 6:

-5000 to -3000	-3000 to -1000	-1000 to 0	0 to 1000	1000 to 3000
0	0	0	100	0

Expert 7:

0 €$_{2008}$

Figure 4.22: Experts' CPT for 2030 BEV Cost Increment (€$_{2008}$)

All seven experts gave probability assessments for 2030 BEV cost increments. As can be seen from the tables in Figure 4.22, experts did not make changes to the categories, except for expert 7, who said that the BEV cost difference to current ICE was 0 €$_{2008}$. However, he said that BEV could become expensive if battery costs stayed high because in that case, lightweight BEV would have to be built in order to reduce energy consumption.

Expert 1 was the only one to use the highest category of 1000 to 3000 €$_{2008}$, to which he assigned 100 per cent probability, and expert 3 was the only one who attributed some probability to the lowest cost category of -5000 to -3000 €$_{2008}$. Expert 3 explained that BEV would be relatively cheap, because they could do without many of the components needed for ICE. However, ancillary units and heating systems could become expensive.

Figure 4.23 shows that much probability concentrates on the cost range of -3000 to 1000 €$_{2008}$. Four experts attributed 100 per cent probability to a single category or even a single value. Apparently, experts who depicted BEV as small city vehicles do not necessarily expect the vehicles to become cheaper than experts who demand them to be longer-range vehicles. For example, the two highest cost estimates (and the only estimates with 100 % of probability

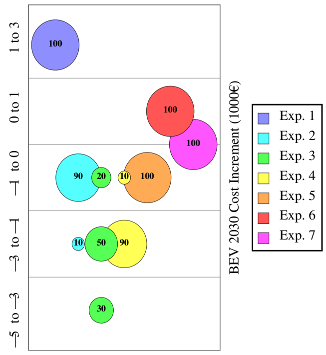


Figure 4.23: Bubblegraph for BEV Incremental Costs

weight on positive cost differences to current ICE) come from experts 1 and 6, who share the image of city BEV. In contrast, expert 7 who demands BEV ranges of 300 to 400 km, assessed BEV vehicle cost increment to be zero.

4.4.3.10 PHEV Sales relative to ICE

Finally, to complete the assessment of the 2030 German new passenger vehicle fleet, sales shares of the different vehicle types were elicited. To allow treating sales shares of the different vehicle types one by one while assuring that they sum up to 100% for the overall fleet, ICE sales were used as a basis and sales of all other vehicle types were asked for in the form of units sold per 100 ICE sold. This way of modeling allows to deduce market shares in a calculative step as described in Section 4.3.

First, experts were asked to fill in CPT for the number of PHEV sold per 100 ICE in 2030. In the BBN, PHEV sales depend on the annual average cost difference of a PHEV compared to an ICE. The annuities are calculated within the BBN on the basis of annual depreciation and annual variable costs (for the details, see Section 4.3). Four states were proposed for the annual cost difference of PHEV to ICE:

- -3000 to 0 €$_{2008}$
- 0 to 2000 €$_{2008}$
- 2000 to 5000 €$_{2008}$, and
- 5000 to 8000 €$_{2008}$.

As PHEV can be driven in ICE mode once the energy stored in the battery has been consumed, electric range is no possible drawback for PHEV in comparison to ICE and was not used as a parent. For PHEV sales per 100 ICE sold, four categories were originally introduced in the BBN, namely

- 0 to 10,
- 10 to 70,
- 70 to 130, and
- 130 to 200 PHEV per 100 ICE.

Thus, states range from no PHEV sold to twice as much PHEV sold as ICE. Only three experts provided an assessment of PHEV sales shares. As described before, experts 1 and 4 did not consider PHEV in their BBN. Two more experts (experts 6 and 7) were not ready to assign 2030 sales shares, neither for PHEV nor for any other vehicle type. Expert 6 argued that too many preconditions would have to be known to give such an assessment, including possible restrictions in place for accessing certain areas, e.g., vehicle noise standards for cities, or the characteristics of the car taxation system. Expert 7 also pointed out that too much would have to be assumed, e.g., policy incentives, customers' willingness to pay, and the development of the climate debate and consumer consciousness. He added that battery development would decide on the fate of PHEV versus BEV: If they developed well, only BEV would be sold and no PHEV, and vice versa in case of poor development.

Figure 4.24 shows the CPT specified by three experts. While experts 2 and 3 have used the categories proposed, expert 5 has subdivided the lowest PHEV sales category into two subcategories of 0 to 5 and 5 to 10 PHEV per

Expert 2:

PHEV annual cost difference to ...	0 to 10	10 to 70	70 to 130	130 to 200
-3000 to 0	0	0	0	100
0 to 2000	100	0	0	0
2000 to 5000	100	0	0	0
5000 to 8000	100	0	0	0

Expert 3:

PHEV annual cost difference to ...	0 to 10	10 to 70	70 to 130	130 to 200
-3000 to 0	0	0	0	100
0 to 2000	10	20	60	10
2000 to 5000	70	20	10	0
5000 to 8000	100	0	0	0

Expert 5:

PHEV annual cost difference to ...	0 to 5	5 to 10
2000 to 5000	0	100
5000 to 8000	100	0

Figure 4.24: Experts' CPT for 2030 PHEV Sales per 100 ICE Sold (No. of Cars)

100 ICE sold. He thought that larger sales figures were unrealistic. Of the cost categories, he only considered the highest two, stating that the PHEV markup on ICE annual costs could not be expected to be lower than 2000 €$_{2008}$.

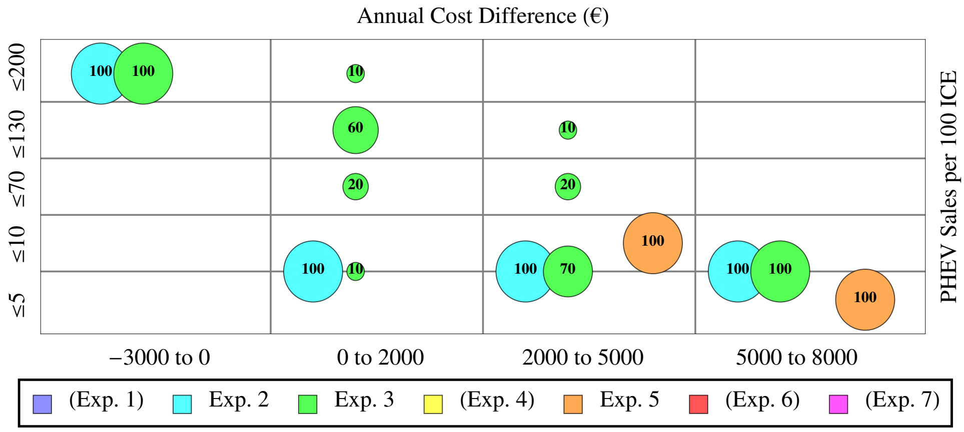


Figure 4.25: Bubblegraph for PHEV Sales

In order to accommodate for the assessment of expert 5, his subdivided categories have been used in the bubble chart in Figure 4.25. The assessments of experts 2 and 3 relating to the original category of 0 to 10 PHEV per 100 ICE have been placed on the boundary of the two new categories.

As Figure 4.25 shows, experts 2 and 3 admitted the option of PHEV annual costs lower than ICE annual costs, and both gave a 100 % probability to PHEV sales higher than ICE sales in that case. While expert 2 thinks that PHEV sales will be 0 to 10% of ICE sales if their annual costs are higher, expert 3 still attributes some probability to larger PHEV sales shares at annual cost increments of up to 5000 €$_{2008}$.

All three experts place probability mass in a diagonal way from top-left to bottom-right, which shows that they agree that increasing annual excess costs over ICE reduce the sales share of PHEV.

4.4.3.11 BEV Sales relative to ICE

In analogy to PHEV sales, experts were asked to reveal their conditional probabilities for 2030 BEV sales. BEV sales were to be specified relative to ICE sales, as well.

BEV are modeled as dependent on two parent variables, namely their annual user cost difference to current ICE and their range. To keep the size of CPT manageable, the number of states of the parent variables had to be reduced to a minimum. This led to a relatively coarse set of three categories for annual user cost increments of BEV compared to ICE, namely

- −5000 to 0 €$_{2008}$,
- 0 to 4000 €$_{2008}$, and
- 4000 to 8000 €$_{2008}$.

The number of states for the range BEV can cover with one charge of the battery was limited to two, i.e.,

- 30 to 200 km, and
- 200 to 500 km.

For the variable in question, BEV sales per 100 ICE sold in 2030, the three categories of 0 to 5, 5 to 10, and 10 to 30 were proposed to the experts.

Expert 1:

BEV annual cost difference to I...	BEV range (km)	0 to 5	5 to 10	10 to 30
0 to 4000	100	0	10	90
4000 to 8000	100	0	30	70

Expert 2:

BEV annual cost difference to I...	BEV range (km)	0	0 to 5	5 to 10	10 to 30	30 to 100
-5000 to 0	0 to 100	100	0	0	0	0
-5000 to 0	100 to 200	0	0	10	40	50
-5000 to 0	200 to 500	0	0	0	0	100
0 to 4000	0 to 100	100	0	0	0	0
0 to 4000	100 to 200	0	100	0	0	0
0 to 4000	200 to 500	0	80	20	0	0
4000 to 8000	0 to 100	100	0	0	0	0
4000 to 8000	100 to 200	0	100	0	0	0
4000 to 8000	200 to 500	0	100	0	0	0

Expert 3:

BEV annual cost difference to I...	BEV range (km)	0 to 5	5 to 10	10 to 30
-5000 to 0	25.0962 to 200	10	20	70
-5000 to 0	200 to 500	0	10	90
0 to 4000	25.0962 to 200	80	20	0
0 to 4000	200 to 500	10	30	60
4000 to 8000	25.0962 to 200	100	0	0
4000 to 8000	200 to 500	90	10	0

Expert 4:

BEV annual cost difference to I...	0 to 5	5 to 10	10 to 30
-2000 to 0	20	80	0
0 to 2000	90	10	0

Expert 5:

BEV annual cost difference to I...	0 to 5	5 to 10	10 to 30
0 to 2000	0	100	0
2000 to 4000	100	0	0

Figure 4.26: Experts' CPT for 2030 BEV Sales per 100 ICE Sold (No. of Cars)

The resulting CPT was filled in by five experts as presented in Figure 4.26. Experts 6 and 7 were unwilling to provide sales share estimates. They argued that there was too much uncertainty on influencing factors not explicitly specified in the BBN, as explained in more detail in the previous section.

Of the five experts who have specified CPT, only two (experts 2 and 3) accepted BEV range as an influencing factor for BEV sales. For both, probabilities of higher sales shares increase with an increasing range. Expert 2 added additional sales categories at both ends of the category scale proposed: 0, and 30 to 100 BEV sold per 100 ICE. He also changed the set of ranges to contain three states, namely 0 to 100, 100 to 200, and 200 to 500 km. At a range of 0 to 100 km, he was sure that no BEV would be sold, at all. In contrast, at negative costs and with ranges of more than 100 km, he attributed high probabilities to his newly created category of 30 to 100 BEV sold per 100 ICE. This means that he saw a chance for BEV to sell up to as much as ICE do. Expert 3 sticked to the proposed scheme of categories.

Experts 1, 4, and 5 said that BEV range was no appropriate parent variable for BEV sales. Expert 1 said that 2030 BEV would be designed such that they had a range of about 100 km. Ranges of 200 km and more were discarded as unrealistic. Similarly, expert 4 assumed 150 km to be a maximum range for BEV, and expert 5 said that only ranges of 100 to 150 km were imaginable. Thus, for all three experts, BEV range is more or less given and not an argument with a major impact on sales shares.

In regard to the annual cost difference of a BEV compared to an ICE, all five experts agreed that it influenced BEV sales. At higher costs, probabilities move towards lower sales shares for all of them. The estimates of customers' willingness to pay for BEV, however, differentiated strongly among experts. Experts 4 and 5 could not imagine BEV sales higher than 5 to 10 per cent of ICE sales under any circumstances. In contrast, expert 1 gave a more than 50 per cent probability to BEV sales in the range of 10 to 30 per cent of ICE sales even in case of a high cost markup.

Figure 4.27 presents the probability assessments as bubbles. As many experts made changes to the category scheme, it was difficult to assemble all assessments within one chart.

For annual cost differences (placed on the x-axis), experts 4 and 5 have used their own categories: Expert 4 considered the original categories as too far-spread and used -2000 to 0 and 0 to 2000 €$_{2008}$, instead. Expert 5 expected cost differences to be positive and introduced the categories of 0 to 2000 and 2000 to 4000 €$_{2008}$. In Figure 4.27, these changes have been accommodated, using categories of -5000 to -2000, -2000 to 0, 0 to 2000, 2000 to 4000, and

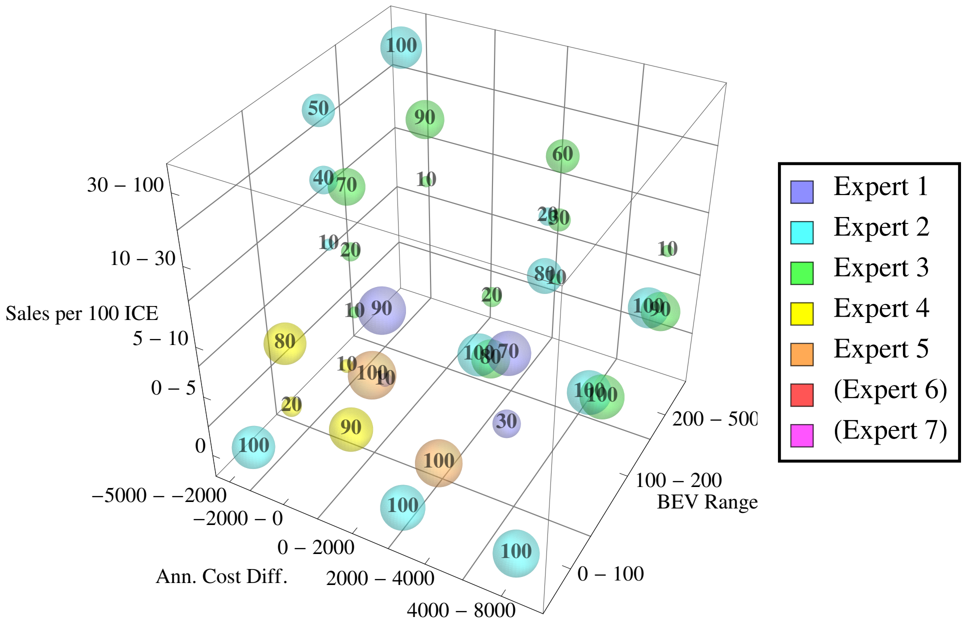


Figure 4.27: Bubblegraph for BEV Sales
x-axis: BEV Annual Cost Difference to ICE (Euro p.a.), **y-axis:** BEV Range 2030 (km), **z-axis:** BEV Sales per 100 ICE.

4000 to 8000 €$_{2008}$. Assessments in the originally lowest category of −5000 to 0 €$_{2008}$ have been placed roughly on the boundary between the lowest two categories (at −2000 €$_{2008}$), and those in the original class of 0 to 4000 €$_{2008}$ have been placed on the boundary between the third and fourth category (at 2000 €$_{2008}$).

For BEV ranges (y-axis), the categories proposed by expert 2 have been used for the figure. The assessments of experts 1, 4 and 5, who expect fixed modest BEV ranges, have all been included into the lowest category (0 to 100 km). States for BEV sales (z-axis) have been used as suggested by expert 2, as well. They include all original categories plus the two this expert added.

4.4.3.12 Other Vehicles' Sales relative to ICE

Finally, experts were asked to specify what shares of vehicles other than ICE, PHEV and BEV they expected to be part of the 2030 German new car fleet. This was done because only a subset of thinkable vehicle technologies is explicitly modeled in the BBN. In order to get a complete picture and to get proportions right, other vehicles were introduced as a catch-all variable without specifying what technologies exactly are meant.

Expert 1:

0 to 5	5 to 10	10 to 30
100	0	0

Expert 2:

0 to 5	5 to 10	10 to 30
80	20	0

Expert 3:

0 to 5	5 to 10	10 to 30
0	0	100

Expert 4:

0 to 5	5 to 10	10 to 30
20	80	0

Expert 5:

0 to 1	1 to 10	10 to 30
100	0	0

Figure 4.28: Experts' CPT for 2030 Other Vehicles Sales per 100 ICE (No. of Cars)

As these vehicles are not modeled in detail, their market share was conceived as an orphan variable without direct influence from other variables in the BBN. Other vehicles' market shares were, again, modeled in terms of percentages of ICE sales in 2030. Three categories were suggested, 0 to 5, 5 to 10, and 10 to 30 other vehicles per 100 ICE sold.

In Figure 4.28, experts' probability tables can be seen, and Figure 4.29 shows them as a bubble chart. As before, experts 6 and 7 refused to quantify market shares. Figure 4.29 shows that most probability mass is placed in the lowest category of 0 to 5% of ICE sales. Two experts, experts 1 and 5, give 100% of probability to other sales in this category. Expert 5 added that he did not see any other vehicle technology of importance.

Expert 3, in contrast, put a full 100% into the highest category of 10 to 30% of ICE sales. Thus, he gave a more optimistic assessment than for BEV sales. He pointed out that the vehicle technology he referred to was the hydrogen fuel cell vehicle (HFCV), which should be considered an option because the major

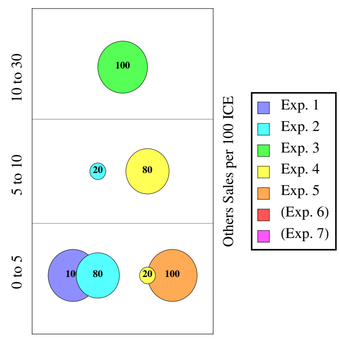


Figure 4.29: Bubblegraph for Other Vehicles' Sales

problems of workability had been solved. Still, infrastructure as well as fuel cell and hydrogen production were unsolved problems, but in case of rising fuel prices, HFCV could be an option.

The remaining two experts, experts 2 and 4, allocated probability mass to the two lower categories. Expert 4 had eliminated PHEV from his BBN because he expected them not to play a significant role in the 2030 new car fleet. He pointed out that the 0 to 10% of 'others' he expected were composed of HFCV and PHEV, with a minor contribution of the latter.

4.4.4 Evaluation of the BBN by the Experts

In each interview, once the elicitation of CPT was completed, the BBN was compiled and discussed with the respective expert. The expert was then asked to evaluate his BBN and the method in general. To this aim, the following three questions were included into the elicitation protocol. Experts were asked to give an answer by checking one of the five boxes for each question:

1. Does the BBN represent the relations between variables appropriately?

   Very appropriately □ □ □ □ □ Not appropriately at all

2. In your opinion, how valid are the quantitative results from the BBN just configured?

   Very valid □ □ □ □ □ Not valid at all

3. Is the method of BBN adequate for examining the development of CO_2 emissions from the German new car fleet until 2030?

   Very adequate □ □ □ □ □ Not adequate at all

Table 4.9 shows the experts' assessments as well as the range, mode and median of all assessments. The assessments made by checking one of the five boxes have been translated into a five-point scale, where five points have been attributed to the first box (very appropriate/valid/adequate), and one point to the last box (not appropriate/valid/adequate at all) for each of the questions.

The values of range, mode and median are to be treated carefully: Experts who were rather skeptic about the BBN presented had a tendency not to answer the evaluation questions at all instead of giving low degrees of confidence. Thus, assessments explicitly given are likely to be biased to the positive side.

As can be seen from Table 4.9, expert 1 judged the BBN, its quantitative results and the method rather favorably. Regarding the structure of variable relations, he said that the part of the BBN used to determine battery energy and weight was not convincing and should be changed. Still, he found quantitative

Table 4.9: Experts' Evaluation of the BBN

	Expert No.							Property of Distribution		
	1	2	3	4	5	6	7	Range	Mode	Median
1. Relations	4	4	4	-	3	2	-	2–4	4	4
2. Results	4	4	5	-	-	4	-	4–5	4	4
3. Method	5	(3)	4	-	-	-	-	3–5	-	4

The assessments are given on a five-point scale, where 1 relates to 'not appropriate at all, not valid at all, not adequate at all' for the three questions, and 5 to 'very appropriate, very valid, very adequate'.

results plausible and said that BBN could be a very good tool for examining the questions at hand.

Expert 2 criticized that there were many premises experts implicitly had in mind when specifying their BBN, which did not become visible. He added that the way of modeling applied here did not correspond to the way engineers think, i.e., comparing costs and saving potentials of different technologies and choosing those which pay off. Still, he attributed four out of five points to both the variable structure and the quantitative results of the model. In regard to the method, he checked the central box but added that he couldn't judge it; therefore, this assessment is put into brackets in Table 4.9.

Expert 3 was very content with the quantitative results his BBN produced. In regard to variable relations, he said that adding a node displaying the willingness of consumers to buy smaller cars would improve the model, as this was a very influential question. He criticized that variable states were very widespread, and model precision could be improved by narrowing down the single categories.

Expert 4 also said that category boundaries were not precise enough, and proposed that it might help to revise the BBN structure in co-operation with an expert on vehicle technology. He also thought that consumer choices should be included explicitly. He did not check any of the boxes asked for and said he could not judge in how far the relations of variables were represented appropriately. He found that the quantitative results from the BBN he had specified were relatively plausible, and that BBN in general were an interesting approach.

Of all seven experts, expert 5 was possibly the most sceptic in regard to the method. He said that it involved too much of 'crystal-ball looking'. Engineers would prefer more tangible assessments, and where these were not available, they would prefer to wait for things to develop. He checked the mean box for the appropriateness of the presentation of variable relations in the BBN, but said he could neither judge the quantitative results of the BBN specified nor the usefulness of the method.

Expert 6 was not content with the depiction of variable interrelations in the model and suggested to have it cross-checked by an engineer. He attributed two points, i.e., said that relations were represented rather inappropriately. In contrast, he found quantitative results relatively valid. In regard to the adequacy of the method, he thought he did not know the method well enough and abstained from a judgement. Due to an inconsistency in the specification of batteries, parts of the model specified by expert 6 did not run properly when presented to the expert and had to be clarified later.

As expert 5, expert 7 expressed major reservation in regard to the method. He said interdependencies were not well specified in the BBN because too many variables of major importance had not been made explicit. The method might be used if linked to complete scenarios specifying economic development, energy prices, population growth and so on, which would offer a complete framework for different experts to make comparable assessments. As the expert specified only the nodes for incremental costs, the BBN could not be run during the interview and no quantitative results were achieved. He did not check any of the boxes proposed.

4.4.5 Model Inconsistencies, Gaps, and Patches

During elicitation, some experts made changes to variables or their states (or assigned zero probability to some states), which was, in principle, intended. However, in some cases this led to model inconsistencies which were not discovered or could not be fixed instantaneously during the interview.

In two cases, experts were so kind to check and alter one or two CPT when contacted by email after the interview. For both experts, the new tables have been documented in the description of the previous sections (instead of the originally elicited ones). During elicitation, expert 2 limited PHEV battery weight to 100 kg. However, his CPT for PHEV battery energy contained positive probability for battery energy too high to be contained in a 100 kg battery under the unfavorable battery energy density scenario. He corrected his assessment of PHEV battery energy slightly downward, providing the new CPT which has been included in Figure 4.14, and allowed for up to 160 kg of PHEV battery in some rare cases.

In the BBN specified by expert 6, an opposed problem occurred. Expert 6 had eliminated the lowest battery weight categories for both PHEV and BEV, setting PHEV battery weight to at least 100 kg and BEV battery weight to at least 200 kg. However, with the CPT for BEV and PHEV energy he had originally specified, lower battery weights for PHEV and BEV had positive probability under the favorable battery energy density scenario. Expert 6 shifted his assessment towards higher battery energy, providing the new CPT which can be seen in Figures 4.14 and 4.16.

In the BBN quantified by expert 5, a consistency problem occurred, as well. When filling in sales share CPT, he excluded annual cost increments of PHEV compared to ICE lower than 2000 $€_{2008}$, as well as annual cost increments for BEV lower than 0 $€_{2008}$ (see the assessments of expert 5 included in Figures 4.24 and 4.26). However, the expected value for the PHEV annual cost increment which his BBN produces under the BASE scenario is 1920 $€_{2008}$, and the expected value for the BEV cost increment is just 28 $€_{2008}$ p.a. Thus, the samples generated by the updating mechanism contain many cases for annual cost increments where the expert has not provided any corresponding sales share estimates. The problem is aggravated under the low battery cost (BAT) scenario, which reduces battery costs to 200 $€_{2008}$/kWh. Expert 5 was asked but unwilling to extend his CPT, arguing that no-one could realistically assume future battery costs that low. He said that minimum future battery cost estimates were 250 $€_{2008}$/kWh. In order to make the BBN generally executable, I added a line to expert 5's PHEV and BEV sales shares CPT. I assumed the sales estimate of 5 to 10 % of ICE which the expert attributed at the lowest cost increment he accepted to hold as well in case of still lower costs for both PHEV and BEV. This solution limits PHEV and BEV sales to a level the expert would generally accept as possible under conditions less favorable to their sales, and extends them to cases where conditions become more favorable. Still, it has to be kept in mind that the expert attributes zero probability to the favorable battery cost scenario of 200 $€_{2008}$/kWh, and that the BBN produces results he would not accept if that scenario is chosen.

Apart from model inconsistencies, there are a number of gaps because some experts did not specify all elicitation nodes. For example, as documented above, experts 1 and 4 did not consider PHEV and all nodes relating to PHEV were eliminated from their BBN. In other cases, elicitation gaps were more problematic for BBN executability or results. Two experts (experts 6 and 7) did not fill in any of the sales share CPT. The resulting BBN therefore do not allow to make statements on the composition of the 2030 German new vehicle fleet and on fleet CO_2 emissions, but can only be used to analyze emissions of the different vehicle types separately.

In the BBN of expert 7, an even more vital element is missing, as expert 7 did not specify ICE and PHEV fuel consumption. The resulting BBN is incomplete and can not be run at all without amendment. However, there is some information in it that can be used if an extension is made. I have therefore decided to follow the proposition of 'expert 7a', a colleague of expert 7 who accompanied him for the interview but did not specify a BBN of his own. Expert 7a proposed to use an optimization approach for determining vehicle fuel consumption. As this proposal was not rejected by expert 7, I have added an optimization routine determining the most cost-efficient fuel consumption level of 2030 ICE and PHEV to make the BBN executable. Of course, it has to be kept in mind that the BBN contains elements added by me ex-post and that its functioning has not been demonstrated to the expert, as it took some time to add the optimization. Thus, it is unclear in how far the BBN represents the expert's view.

The optimization implemented works as follows: For determining ICE and PHEV fuel consumption, I have assumed that the aim of OEM is to minimize annual user costs of its cars in order to make them competitive. This implies the somewhat doubtful assumption that the predominant argument for consumers vehicle choice is user costs. Annual user costs result as the sum of an annual amortization rate (r) of initial costs and annual variable costs.

In regard to initial costs, the price increment of 2030 car types over today's standard vehicles has been modeled in the BBN, but overall costs are not included. This poses no problem for the present optimization, because only cost increments are assumed to be linked to fuel consumption, and the basic price of today's vehicles does not impact the result. Assessments of incremental costs (IncrCost) of 2030 vehicles compared to current ICE have been specified by expert 7 as documented in sections 4.4.3.7 and 4.4.3.8. Vehicles are more expensive the lower their fuel consumption (fc).

A second component of initial costs is a penalty (p) which may apply if a CO_2 emission limit (CO2lim) imposed through regulation is surpassed. Apart from fuel consumption, CO_2 emissions depend on the CO_2 intensity of fuel (CO2int).

As regards variable costs, a higher fuel consumption translates into higher variable costs, depending on the fuel price (fp) and the distance driven in a year (dist). All assumptions on possible CO_2 emission limits and penalties, CO_2 intensity of fuel, fuel prices, annual driving distances and the amortization rate are as described in the respective paragraphs of Section 4.2.

Optimization can now be applied to determine the cost-minimizing level of ICE and PHEV fuel consumption. The equations used for calculating the fuel consumption of ICE and PHEV in the BBN of expert 7 are as follows:

$$\underset{\mathrm{fc_{ICE}}}{\mathrm{Min!}} \quad \left\{\mathrm{IncrCost_{ICE}} + \max\left[0, \left(\frac{\mathrm{fc_{ICE}}}{100} * \mathrm{CO2int} - \mathrm{CO2lim_{ICE}}\right) * \mathrm{p}\right]\right\} * \mathrm{r} + \mathrm{fc_{ICE}} * \mathrm{fp} * \frac{\mathrm{dist}}{100}$$

$$\underset{\mathrm{fc_{PHEV}}}{\mathrm{Min!}} \quad \left\{\mathrm{IncrCost_{PHEV}} + \max\left[0, \left(\frac{\mathrm{fc_{PHEV}}}{100} * \mathrm{CO2int} - \mathrm{CO2lim_{PHEV}}\right) * \mathrm{p}\right]\right\} * \mathrm{r} + \mathrm{fc_{PHEV}} * \mathrm{fp} * \frac{\mathrm{dist}}{100}$$

As the BBN works with continuous variables discretized into a number of states, optimization can not be continuous, either, but selects the cost-minimizing states for ICE and PHEV fuel consumption at a given instantiation of the other variables.

4.4.6 Elicitation Conclusions

Eliciting seven experts, a set of seven individually specified BBN on the 2030 German new vehicle fleet has been created. Five of them are complete in the sense that they contain an experts' assessments of all four groups of variables asked for: battery characteristics, fuel and energy consumption, vehicle costs, and sales shares. The remaining two BBN lack experts' statements on sales shares, thus information contained in them can not be condensed into an average assessment for the 2030 new vehicle fleet. Moreover, one of the two also lacks an expert's probability distributions for ICE and PHEV fuel consumption, which have been replaced by an optimization routine.

Eliciting subjective probabilities of experts in regard to a question the answer of which can not be known today, but depends on many factors the development of which is uncertain, was a largely experimental endeavor. During elicitation, apart from asking for CPT, I made some more general observations in regard to experts' reaction to the research method. First of all, I was encouraged by the willingness of many experts to give the method of an expert-based BBN a try. Second, in many cases, experts gave much less widespread CPT assessments than I had expected. Most of them focussed on one or two states in each line of the CPTs, setting probabilities of further states to zero. This phenomenon may be linked to the bias of overconfidence, a problem that tends to occur in expert elicitation (see Section 2.5.3).

In regard to the interview procedure, I found that it was possible but demanding to do the whole interview within one hour. With experts who felt at home in the subject area and with many of the CPT similarly structured, the interview as outlined in the elicitation protocol turned out to be feasible. However, with experts who specified all CPT, there was little time left for demonstrating BBN runs and asking for feedback.

Many experts revealed some of the additional assumptions that governed their assessments. As a single interviewer, it was difficult to fill in the CPT on the laptop, make the necessary changes to the BBN, and keep track of the storyline shaping an expert's expectations, simultaneously. I have focussed on getting the numbers right, but this means that I may not have recorded many of the implicit assumptions revealed. If done again, similar interviews would benefit if there was a team of two interviewers, more time could be accorded for the interview, or less CPT were to be elicited.

4.5 Results from Running the BBN: Scenario Analysis

In this section, results from executing the seven BBN specified by the experts are presented and discussed. A first step after completing elicitation, which has also been carried out during the interviews, is to compile the BBN without any further inputs (of course, the calculative nodes need probability tables which have to be filled in as prescribed by their equations, first). The CPT provided by the experts are processed along with all information contained in the network. In the absence of any further 'findings' entered into the BBN, an uniform probability distribution over all states is assumed for any parent variable where no distribution has been specified, e.g., the 2020 ICE CO_2 emission limit, or 2030 battery energy density. During the compilation process, the probability tables of all nodes are updated to the state of information contained in the BBN. For the details on the updating mechanism, see Section 2.4.4.3.

As an example, Figure 4.30 shows the BBN of expert 2 after compilation. Policy and technology nodes (colored red and blue), which can be used for entering scenarios, have not been instantiated, thus each of their states has been assumed to be equally likely.

For each node, a probability distribution can be read off. The black bars on the right in a node's panel represent the probability that the variable is in each of its possible states, and numerical values are given. For each node which takes discretized continuous states (as opposed to nodes with discrete, named states), in the bottom line of the node's panel, two values in the form of '$x \pm y$' can be found. For these nodes, x is the expected value (or mean) of the probability distribution, and y is the standard deviation.[14]

Figure 4.30 shows that, with no node instantiated, expert 2's expected value for 2030 German new car fleet emissions is 114 gCO_2/km WTW (see the final node of the BBN).[15] Possible fleet emissions range from below 20 up to nearly 340 gCO_2/km WTW. There is a peak of probability (35.3%) in the category of 100 to 120 gCO_2/km WTW, and the distribution flattens to both sides of the peak. The shape of the distribution for 2030 new ICE CO_2 emissions is similar with its peak in the same category, but a higher expected value of 127 gCO_2/km WTW. For 2030 new PHEV and BEV, expected emission values are 106 and 107 gCO_2/km WTW. For both, much probability mass is placed on low emission categories.

Fleet emissions are derived from the emissions of the different car types, weighed with their shares in the 2030 German new car fleet. In the present BBN and under the presently assumed conditions, ICE are likely to make up for a very large share of 80% and more (nearly 50% of probability), but there is also a chance of nearly 40% that they will contribute only 30 to 40% of the 2030 German new vehicle fleet. Another large chunk possibly goes to PHEV, which are roughly equally likely to make up for either 0 to 10% or for more than 50% of the overall new car fleet. Further vehicle types play a minor role; the chances that BEV or 'other vehicles' contribute more than 5% of 2030 new vehicles is around 10%, each.

The striking result of either up to 10 or more than 50% of PHEV in the 2030 new car fleet is brought about by the expert's assessment of the reaction of PHEV sales shares to user cost differences. As can be seen in Figure 4.30, there is roughly a 50/50 chance that PHEV user costs are higher or lower than annual ICE user costs in 2030, and the expert assumes that users have a strong tendency to choose the cheaper vehicle. With the assumptions currently used, BEV are likely to be equipped with large, expensive batteries, which leads to a cost increment that makes them rather unattractive to users in 2030.

Much more information can be read off from the compiled BBN, e.g.,

- the probability distributions of 2030 ICE and PHEV fuel consumption (ICE are likely to be slightly more fuel consuming than PHEV in ICE mode with expected values of 4.4 and 3.7 l/100km),

[14] Netica calculates the expected value from the exact information available in the BBN. In contrast, for discretized continuous nodes as used in my BBN, the standard deviation is derived considering the probability mass in each category uniformly distributed over its range.

[15] For comparison: This is roughly 60% of WTW CO_2 emissions of the German new car fleet in 2008, which were 195 gCO_2/km.

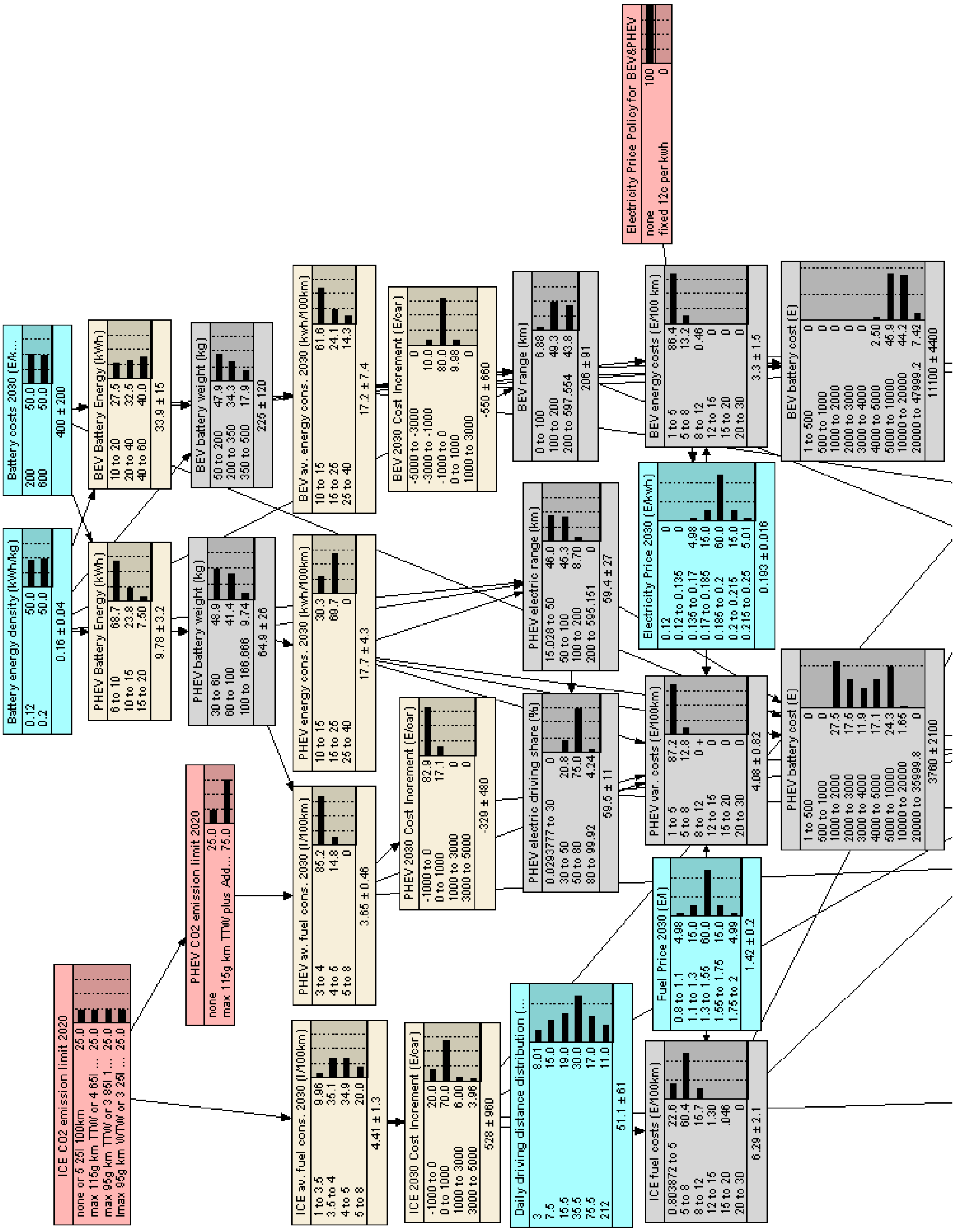


Figure 4.30: An Expert's BBN compiled, upper half

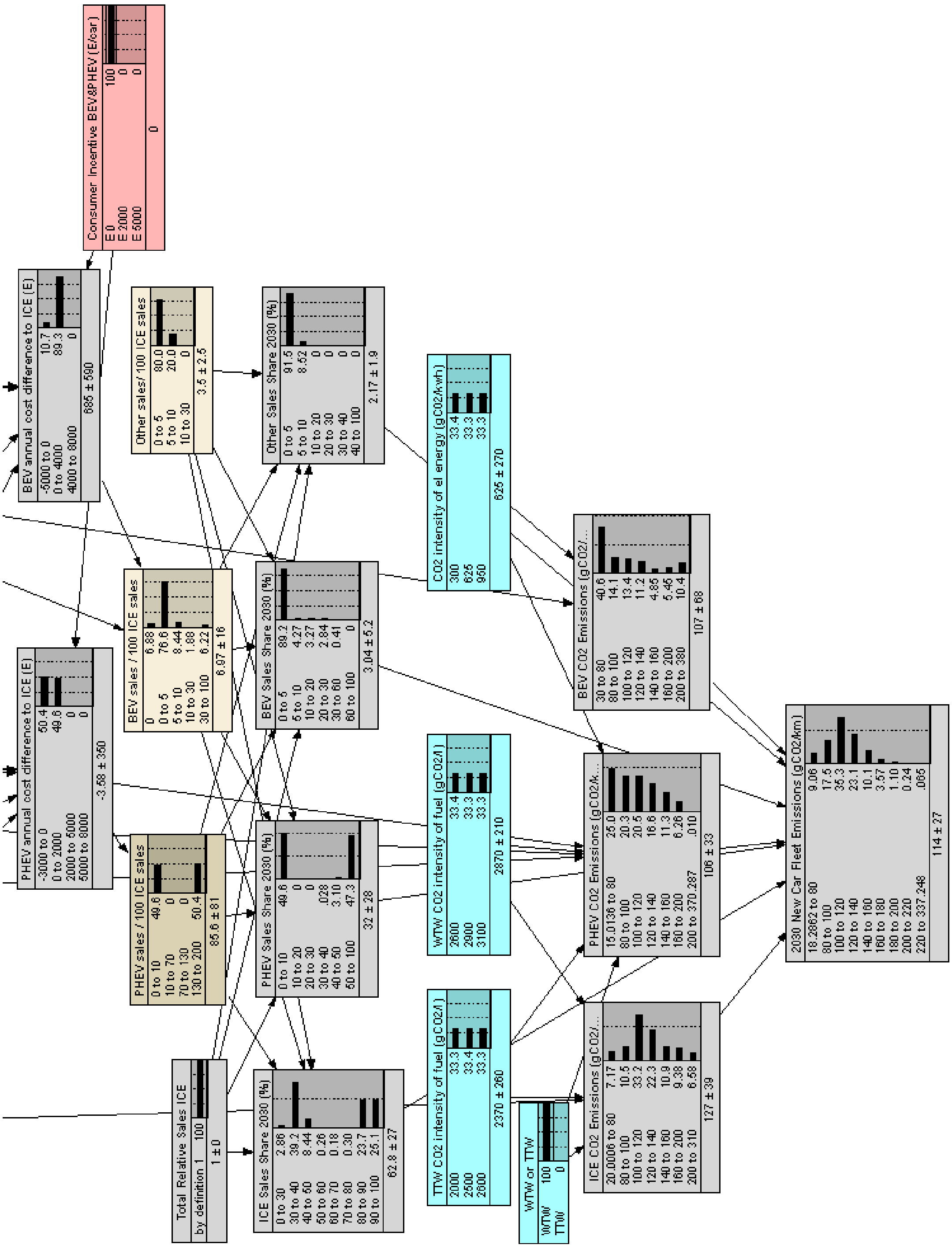


Figure 4.30: An Expert's BBN compiled, lower half

- the distributions of 2030 PHEV and BEV electric energy consumption and their electric ranges (PHEV are unlikely to travel more than 100 km with one charge, while BEV have a more than 40% chance to have a range larger than 200 km), and
- the probability distributions for 2030 vehicle cost increments compared to today's ICE (2030 ICE are likely (probability of 80%) to be more expensive than today's, while the cost increments of BEV and PHEV excluding the battery both have more than 80% chances to be negative).

These are some examples of what can be learned from one expert's BBN with a given setting of parent variables. The aim of this section is to extend the focus to all seven experts' BBN, and to use different scenarios in order to conduct analysis in "what-if..." style: "What if a certain regulation is implemented?", "What if battery technology develops well/poorly?", "What if fuel prices rise strongly?" The assessments of the different experts will be presented together, and their judgement of the effect of certain scenarios can be compared.

Technically, scenario analysis is carried out by instantiating different nodes in the BBN and updating the BBN to that state of 'knowledge'. Basically, the policy, technology and further red and blue nodes in the BBN will be used for creating scenarios. In principle, however, any node in a BBN can be instantiated and it can be left to the updating procedure to derive the combination of states of other nodes which is best compatible with the given setting.

Unfortunately, the present BBN is too large for constructing an inference engine that allows instantaneous updating whenever new information is entered. Instead, a sampling update algorithm will be used which allows for approximate updating and has to be relaunched after entering new information.[16]

The main task with presenting scenario analysis results is to condense information contained in the different BBN such that an overall picture arises and conclusions can be drawn, but without simplifying too strongly or throwing away too much information.

4.5.1 Description of Scenarios

The effects of ten different scenarios have been examined within the seven BBN. As a starting point for scenario analysis, the following baseline (BASE) scenario for 2030 has been defined:

- Regarding European car CO_2 emission regulation, it is assumed that a 2020 regulation tightening current standards will be issued, but that the

[16]Tests I have run suggest that results are slightly less precise than with formal updating, but still at a level of precision which does not interfere with the quality of results.

agreed limit will be interpreted in a relatively weak way. The regulation extends to emissions from ICE as well as to emissions from PHEV in combustion engine mode.

- Battery development will result in a modest decrease of battery prices from today's level and in energy densities at the upper limit of today's best batteries.

- The fuel price will be in the range of the 2008 fuel price, and the electricity price range will be slightly below 2008 prices.

- CO_2 intensities of the fuel mix and of electric energy are assumed to be as in 2008.

- There are no incentives fostering the purchase of PHEV or BEV.

The baseline scenario was intentionally designed to be rather conservative. Parameters were assumed to stick closely to current levels. While the probability of such a development may be debatable, a conservative baseline scenario has several advantages for the present analysis:

- As there is much uncertainty on the development of most of the parameters, e.g., technical, regulatory, and price development, the choice of baseline parameters is much less arbitrary than the definition of a business-as-usual scenario would be.

- Based on the baseline scenario, a number of scenarios can be derived where single parameters develop more dynamically (e.g., better battery development, stricter regulation, lower fuel or electricity CO_2 intensities), and the impacts of these changes can be analyzed by comparison to the baseline scenario. This allows to differentiate the impact of changes in different parameters.

- It can be hypothesized that this baseline is a sort of 'worst case' scenario in regard to the resulting average vehicle CO_2 emissions, and that a more dynamic development of most of the parameters is likely to drive down 2030 German new car fleet average emissions. This hypothesis can be put to the test in the further analysis.

- The baseline scenario examines the effect of future vehicle technology on CO_2 emissions at today's fuel and electricity CO_2 intensities, i.e., it assesses the effect of technological development in an isolated way. This permits to relate the results to the current discussion, e.g., on BEV emissions, which are often proposed to be low even at the current electricity mix.

By varying different parameters, seven basic scenarios are derived from the BASE scenario. The renewables (REN) scenario assumes that in 2030, considerably more renewable energy is used for electricity generation than today. The battery development (BAT) scenario implies that batteries make good progress until 2030, both in regard to improved energy density and in regard to lowered costs. The CO_2 policy (Cpol) scenario is used to examine the case that the EU regulation of 2020 vehicle fleet CO_2 emissions is stricter than in the BASE case. The tightening of regulation regards ICE emissions, but not PHEV emissions. Two further scenarios relate to possible consumer incentives for buying PHEV and BEV; EVInc1 examines the effects of a premium being paid for the purchase of a new PHEV or BEV, and EVInc2 assumes that the price for electric energy used for vehicle propulsion is fixed to a relatively low level. The fuel price (FP) scenario proposes a relatively high fuel price in 2030, and the biofuel (BF) scenario the introduction of relatively large shares of biofuels into the 2030 fuel mix.

After analyzing these scenarios, a further scenario (RBC) has been created which combines the elements that led to the most important fleet CO_2 emission reductions, i.e., renewables, biofuels and EU CO_2 policy. This was done in order to see how low the emissions would get in case of combined measures. Table 4.10 summarizes the above scenarios and specifies parameter values for the parent variables.[17]

Finally, a low CO_2 (LowC) case was generated (not displayed in Table 4.10), which uses the ability of BBN to perform inference in a 'bottom up' manner. Due to the symmetry of Bayes' Rule, BBN have the unique ability to draw inferences from information entered anywhere in the network. Making use of this property, for each BBN, the lowest possible fleet CO_2 emissions were entered as a finding in the node at the bottom of the BBN, with no other node instantiated (no further findings entered). This was done in order to see what is the most probable way to get to the lowest possible emissions within each BBN. The lowest possible level varies over the different BBN. Within one BBN, 2030 fleet average emissions of 30 to 40 gCO_2/km WTW are feasible, 50 to 60 g in another one, one allows for 70 to 80 g, and two for 80 to 90 gCO_2/km WTW as the lowest possible value.

[17]For a detailed description of the choice of parameters implemented in the BBN, see Section 4.2.

Table 4.10: BBN Scenarios

	BASE	REN	BAT	Cpol	EVInc1	EVInc2	FP	BF	RBC
ICE CO_2 limit (g/km)	115[1]	115[1]	115[1]	95[2]	115[1]	115[1]	115[1]	115[1]	95[2]
PHEV CO_2 limit (g/km)	115[3]	115[3]	115[3]	115[3]	115[3]	115[3]	115[3]	115[3]	115[3]
EV Purchase Incentive (€$_{2008}$/car)	none	none	none	none	5000	none	none	none	none
Battery Energy Density (kWh/kg)	0.12	0.12	0.2	0.12	0.12	0.12	0.12	0.12	0.12
Battery Costs (€$_{2008}$/kWh)	600	600	200	600	600	600	600	600	600
Fuel Price (€$_{2008}$/l)	1.30-1.55	1.30-1.55	1.30-1.55	1.30-1.55	1.30-1.55	1.30-1.55	1.75-2.00	1.30-1.55	1.30-1.55
Electricity Price (€$_{ct}$2008/kWh)	18.5-20	18.5-20	18.5-20	18.5-20	18.5-20	12	18.5-20	18.5-20	18.5-20
CO_2-Intensity of Energy (gCO_2/kWh)	625	300	625	625	625	625	625	625	300
WTW CO_2-Intensity of Fuel (gCO_2/l)	2900	2900	2900	2900	2900	2900	2900	2600	2600

[1]Tank-to-Wheel (TTW); 105 TTW for expert 5

[2]Well-to-Wheel (WTW); 95 TTW for expert 5

[3]Tank-to-Wheel (TTW)

In two BBN, no fleet average could be enforced because the experts had not specified 2030 sales shares and thus no fleet composition was available. In one of them, however, emissions for the different car types could be set to values around 50 gCO_2/km, simultaneously. The other one allowed for ICE emissions to go down to roughly 55 g, PHEV emissions to 75 g, and BEV emissions to 65 gCO_2/km, but not at the same time. Within this BBN, the most likely way to reach very low emissions consists in driving down ICE emissions (to its minimum of 55 gCO_2/km) and in assuming that ICE dominate the 2030 new vehicle fleet, as other vehicle types are too expensive to be likely to reach substantial market shares.

In the following section, a short digression is made which offers a justification of the present scenario approach. Then, in Section 4.5.3, results from running the baseline (BASE) scenario within all seven BBN will be presented and discussed in detail. Apart from describing a possible 2030 situation in case no great changes in any of the parameters occur, the description also serves as a point of departure for analyzing what drives down CO_2 emissions, what is the impact of different policies and technology development, and of changes in the CO_2 intensity of electricity and fuels, as brought about within the different scenarios discussed in Section 4.5.4.

4.5.2 A Critique of Scenario Analysis

Before presenting the results derived from the scenario analysis, a short digression is made to discuss criticism of scenario analysis. I have chosen a set of ten scenarios out of infinitely many possible scenarios, without revealing my subjective scenario weights, a practice that has been criticized, e.g., by Morgan & Keith (2008). The authors discuss the quality of projections of future energy use and CO_2 emissions, and show that these have exhibited poor performance in the past. They suggest that scenarios based on detailed storylines are often ineffective in providing input to decisions under uncertainty. Instead, they were likely to produce systematic overconfidence, which increased with the degree of detail of the scenario description.

In the case of my BBN, scenario descriptions are reduced to a minimum, namely their name and the values some root nodes take within them. No explanation is given of how it is assumed that these parameter values will be reached, as they can possibly be attained in many different ways. With this approach, I hope that overconfidence of readers or users may be limited.

A second point addressed by Morgan & Keith (2008) is whether scenarios should come with probability weights. While some authors of scenario analyses may caution against attaching probabilities to single scenarios, Morgan & Keith (2008, p.196) claim that scenarios are useful to decision-makers "precisely because they communicate, in some measure, the analysts judgement about the relative probability of various futures to decision-makers". They argue that analysts would create scenarios on the basis of their personal probability judgements, and should communicate them along with the scenarios. Otherwise, users would ascribe probabilities to the scenarios to make them applicable for analysis or decision-making, implicitly or explicitly.

Applying this line of argument to the scenario analysis done here, I agree up to the point that the scenarios are built on the subjective judgement of their author. In fact, the ranges or values considered for the different parameters are those that I have judged useful after a careful study of literature, and the combinations I have chosen for building scenarios are cases that seemed interesting to me, subjectively, for different reasons (for a justification of the ranges of parameter values considered, see Section 4.2). Infinitely many other scenarios could be generated and run within the BBN.

When building the scenarios, I have not thoroughly thought about how likely it seems to me that each of them will be realized. Although I would not mind going through the exercise of defining my own probability for each of the scenarios discussed in this work and publishing them, I doubt that potential users would benefit greatly if I did so.[18] I have deliberately chosen to leave it to the user to choose scenarios she is interested in, or to define new scenarios that can be run within the BBN, and potentially come up with own judgements of scenario likelihood, unaffected by my personal judgement. However, it would be of interest to build a set of future developments as complete as possible, as Morgan & Keith (2008, p.206) propose, and to see whether the whole range of possible variable values would fit with those in the current version of the BBN.

4.5.3 BBN Outcomes under the Baseline Scenario

In order to represent as much as possible of the information contained in the seven experts' BBN, the complete probability distributions for central variables will be displayed in this section. This allows to depict the uncertainty experts have included into their judgements, which is one of the advantages BBN offer: For any node, a whole probability distribution can be read off, which is more informative than just characterizing it by a mean and standard deviation. However, giving complete distributions requires some space and may result in

[18]Technically, as the BBN currently contains some continuous variables which have been set to point values, any scenario has zero probability. For defining meaningful scenario probabilities, the BBN would first have to be changed to specify intervals for all continuous variables.

lengthy descriptions instead of handy results. There is a trade-off between representing uncertainty as best we can and making clear-cut statements. Therefore, in later sections, information will be condensed, e.g., into expected values and standard deviations.

Results are presented 'bottom up' in regard to the BBN graphics (see, e.g., Figure 4.1), i.e., the central result of 2030 fleet emissions, placed in the bottom node, is presented first. Then nodes further up in the BBN graphics are consulted to explain how fleet emissions have accrued.

4.5.3.1 BASE German New Vehicle Fleet Emissions

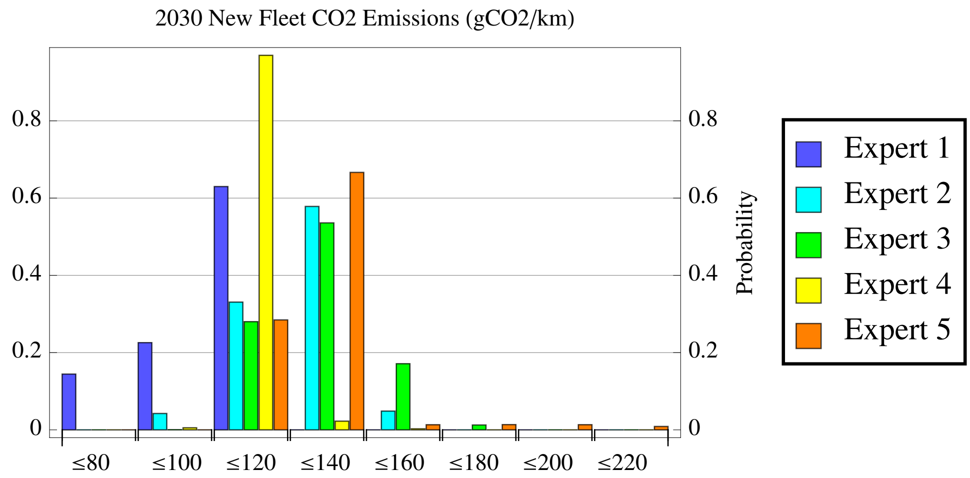


Figure 4.31: BASE 2030 New Vehicle Fleet Emissions (WTW)
Probability distributions of 2030 German new vehicle fleet average CO_2 emissions for experts 1 throughout 5 as derived from their respective BBN under the BASE scenario. For each expert, the same color is used as in the presentation of elicitation results (see Section 4.4.3). The lowest category considered is 20 to 80 gCO_2 WTW, all subsequent categories span 20 g (80 to 100, 100 to 120,..., 200 to 220 gCO_2/km).

Figure 4.31 shows the probability distributions for 2030 German new vehicle fleet average CO_2 emissions which result from processing the experts' inputs along with the parameter values of the baseline (BASE) scenario. This means that they represent the probabilities experts' BBN assign to the respective states of 2030 fleet average emissions, given the world is as described by the BASE scenario. Probability distributions are shown for five experts' BBN. For the remaining two BBN, no fleet distributions could be derived because experts did not provide sales share estimates. As before, emissions are given as well-to-wheel (WTW) figures, which means that they include all emissions over the life cycle of fuel and electric energy (extraction, transport, processing, burning).

As the figure shows, the bulk of probability mass is assigned to 2030 German new vehicle fleet CO_2 emissions of 100 to 140 g/km WTW. All five experts' BBN give a weight of more than 20% to the category of 100 to 120 gCO_2/km, and two of them propose that this category is the most likely one, assigning weights of more than 60% and nearly 100%. In contrast, the remaining three BBN yield that emissions of 120 to 140 gCO_2/km are more likely (weights of more than 50%). Only one expert's BBN accords more than 10% of probability to any emission category lower than 120 g, and another one to emissions higher than 140 gCO_2/km. This shows that the experts' assessments of 2030 CO_2 emissions are relatively consistent.

These figures can be compared to current German new vehicle emissions. In 2008, tank-to-wheel emissions of the German new fleet were 165 gCO_2/km (KBA 2010). As can be deduced from Table 4.1, to get from tank-to-wheel CO_2 emissions to WTW emissions, 17.6% have to be added for gasoline, and 18.7% for diesel fuel. As a rough average, I add 18% or 30 gCO_2/km, resulting in WTW emissions of 195 gCO_2/km for the German 2008 new vehicle fleet. Compared to this value, CO_2 emissions of 100 to 140 g/km WTW as suggested by the BBN to be very likely in the 2030 new fleet under BASE translate to about 50 to 70% of the CO_2 emissions of the 2008 new fleet.

For some readers, vehicle fuel consumption may be a more common measure than CO_2 emissions per kilometer, which are focussed in the present approach. At given carbon intensities of fuel, fuel consumption translates directly into emissions and vice versa. For comparison, it can be said that at today's level of fuel carbon intensity, which is roughly 2470 gCO_2/l_{fuel} TTW (see Section 4.2.5), thus roughly 2915 gCO_2/l_{fuel} WTW, fleet emissions of 100 to 140 gCO_2/km WTW translate into a fuel consumption of 3.4 to 4.8 l/100km. The 2008 German new vehicle fleet average fuel consumption was 6.63 l/100km (KBA 2010).

4.5.3.2 BASE Vehicle Type Emissions

Fleet emissions are derived from emissions caused by the different vehicle types, weighted by their share in the 2030 new vehicle fleet. Figure 4.32 shows the probability distributions for emissions caused by ICE, PHEV and BEV, the three vehicle types explicitly modeled in the BBN, under the BASE scenario. In contrast to fleet emissions, for which assessments of five experts were available, all seven experts have provided enough information for calculating 2030 emissions for distinct vehicle types.

For ICE (first panel), the picture is similar to that for overall fleet emissions just discussed. The BBN place much probability weight on 2030 ICE emissions between 100 and 140 gCO_2/km. Compared to fleet emissions, experts' BBN

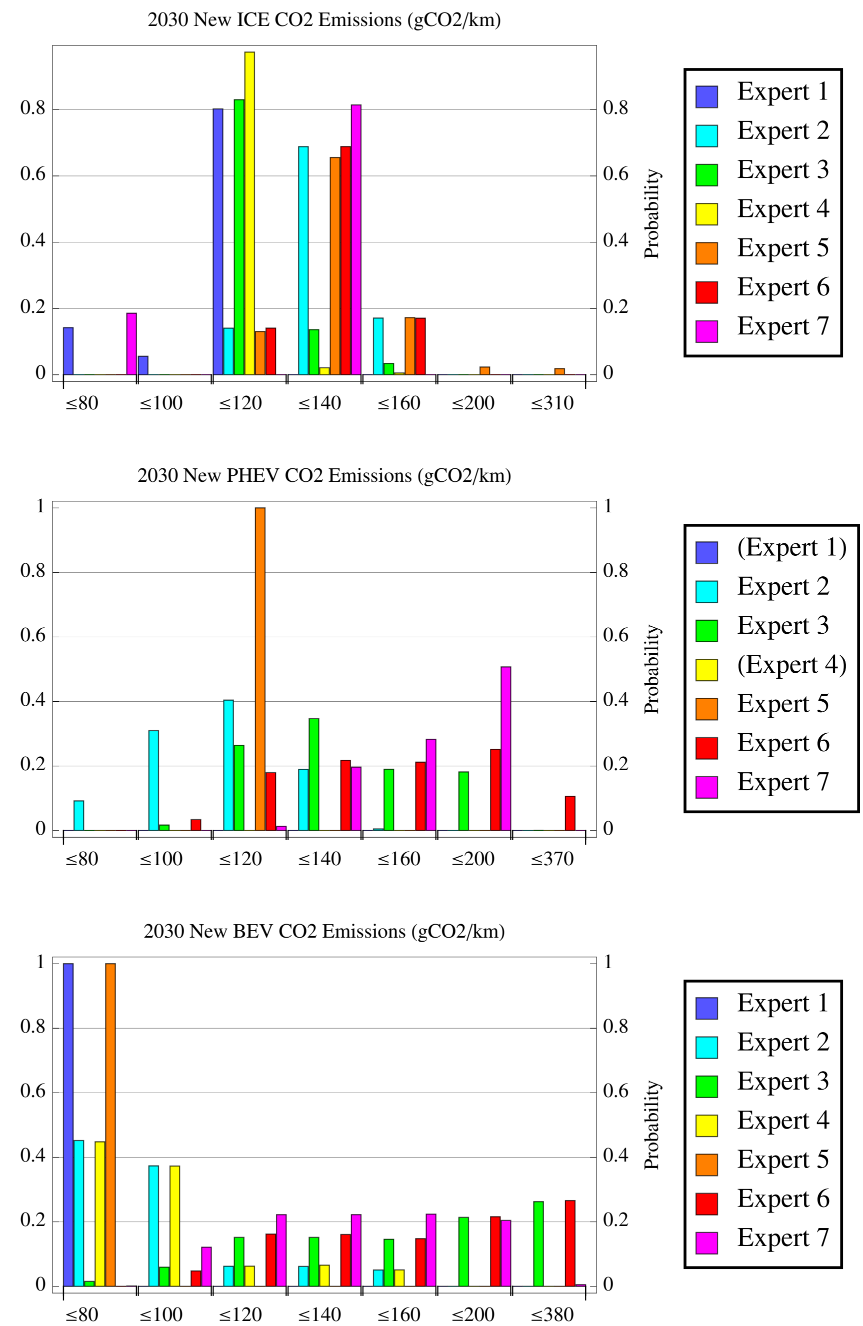


Figure 4.32: BASE 2030 Vehicle Type Emissions (WTW)

Probability distributions of 2030 ICE, PHEV and BEV average CO_2 emissions for all seven experts as derived from their respective BBN under the BASE scenario. The boundary of the lowest emission category varies over car types and among experts: For ICE, the lowest emission category is 20 to 80 gCO_2/km for expert 1 and 45 to 80 gCO_2/km for expert 7 (all other experts do not consider ICE emissions below 100 gCO_2/km). For PHEV, it is 15 to 80 gCO_2/km, and for BEV 30 to 80 gCO_2/km for all experts. All subsequent category boundaries are as indicated on the x-axis of the respective panels. Most categories span a range of 20 gCO_2/km, but the two highest emission categories for all vehicle types cover larger ranges.

are more decided in that each of them strongly favors one of the two categories within this interval. Three BBN (those of experts 1, 3 and 4) attribute probabilities of 80% and more to emissions in the range of 100 to 120 gCO_2/km, while four BBN (those of experts 2, 5, 6 and 7) assign more than 60% of probability to 120 to 140 gCO_2/km. Two BBN give 15 to 20% of probability to lower ICE emissions in the range of 20 to 80 gCO_2/km, while three assign a similar probability to 2030 ICE emitting 140 to 160 gCO_2/km. Other categories, especially those of emissions beyond 160 gCO_2/km, are assigned very little probability.

Regarding PHEV (second panel in Figure 4.32), probability mass is spread much further than for ICE. The category of 100 to 120 gCO_2/km looks like a peak of cumulated probabilities, with all five experts' BBN[19] assigning at least some probability, one of them putting a full 100% into this category (expert 5), another one 40% (expert 2), and the BBN of two experts assigning around 20%. However, all categories from 100 to 200 gCO_2/km receive non-zero probabilities from at least three experts' BBN, and the extreme low (15 to 80 gCO_2/km) and high categories (200 to 370 gCO_2/km) still have probabilities of roughly 10% within one BBN, each.

For BEV (third panel in Figure 4.32), probability mass is widespread, with some experts' BBN focussing on low emissions. Two BBN (those of expert 1 and 5) put a hundred percent of probability onto the category of 30 to 80 gCO_2/km, and two more (experts 2 and 4) assign more than 40% to this category. All categories up to 160 gCO_2/km receive positive probability from five experts' BBN. Three BBN (those of experts 3, 6 and 7) give more than 20% of probability to the category of 160 to 200 gCO_2/km, and the high-end category of 200 to 380 gCO_2/km still receives more than 20% of probability from two of them.

In summary, it can be said that experts' 2030 emission estimates coincide best for ICE, where they concentrate on a rather small range, and diverge most for BEV. For PHEV, the low and high extremes receive less attention than for BEV, and there is a slight focus on medium categories, but assessments are still much more widespread than in regard to ICE. Possibly, the fact that ICE are a well-known technology has led the estimates of their 2030 emissions to converge, while for BEV, there exists no common picture of what applications they will be built for and what standards they have to fulfill.

The distribution for fleet emissions shown in the previous section is most similar to that for ICE emissions, which may be caused by a large weight of

[19]Two experts think that no important number of PHEV will be sold in 2030 and therefore have eliminated them from their BBN.

ICE within the fleet mix. In order to examine this hypothesis, 2030 sales shares of the different vehicle types will be discussed next.

4.5.3.3 BASE Sales Shares

Figure 4.33 shows 2030 sales shares of the different vehicle types under the BASE scenario. The assessments of experts 1 throughout 5 are included, while the remaining two experts did not provide any sales share assessments.

As can be seen, for ICE (first panel), much probability mass cumulates in the two highest sales share categories of 80 to 90 and 90 to 100%. Four of the five BBN assign probabilities of roughly 70 to 100% to ICE making up for at least 80% of the 2030 German new vehicle fleet. One BBN (that of expert 3) yields that 40 to 50% is the most likely category for the 2030 ICE sales share, assigning a weight of about 40%. This BBN, as well as a second one (that of expert 2), also gives roughly a 20% chance to an ICE sales share of 30 to 40%. ICE sales shares lower than 30% have near zero probability within all BBN.

The probability distributions for PHEV sales shares can be seen in the second panel of Figure 4.33. As explained, experts 1 and 4 have eliminated all PHEV nodes from their BBN, arguing that they will be of negligible importance in 2030. To represent this judgement, I have added 100% probability bars to the lowest category of 0 to 10 % for experts 1 and 4. It has to be kept in mind that their sales share assessments are rather close to zero, and surely do not reach 10%. Adding these bars results in a clear dominance of low PHEV sales share estimates. Apart from the BBN of experts 1 and 4, there is a third one (that of expert 5) which assigns a complete 100% of probability to the lowest sales share category, and a fourth one which attributes nearly 80% to it (expert 2). However, two BBN propose to consider higher PHEV sales shares. Complementary to the weights they have assigned to relatively low ICE shares, the BBN of experts 2 and 3 both accord probabilities of 20% to PHEV making up for more than 50% of the 2030 German new vehicle fleet. Within expert 3's BBN, the single most likely category for the PHEV sales share is 40 to 50%, which has a weight of 30%.

Regarding BEV sales shares (third panel in Figure 4.33), much probability mass is assembled in the lower categories, and cumulated probability decreases from the lowest towards higher categories. Three experts' BBN (experts 2, 3 and 4) suggest that shares of 0 to 5% are most likely (weights of more than 70%), and expert 5's BBN assigns an 80% probability to BEV sales shares of 5 to 10%. The BBN of expert 1 gives a 60% weight to BEV comprising 10 to 20% of 2030 new vehicles, and 20% to BEV making up for 20 to 30% of the

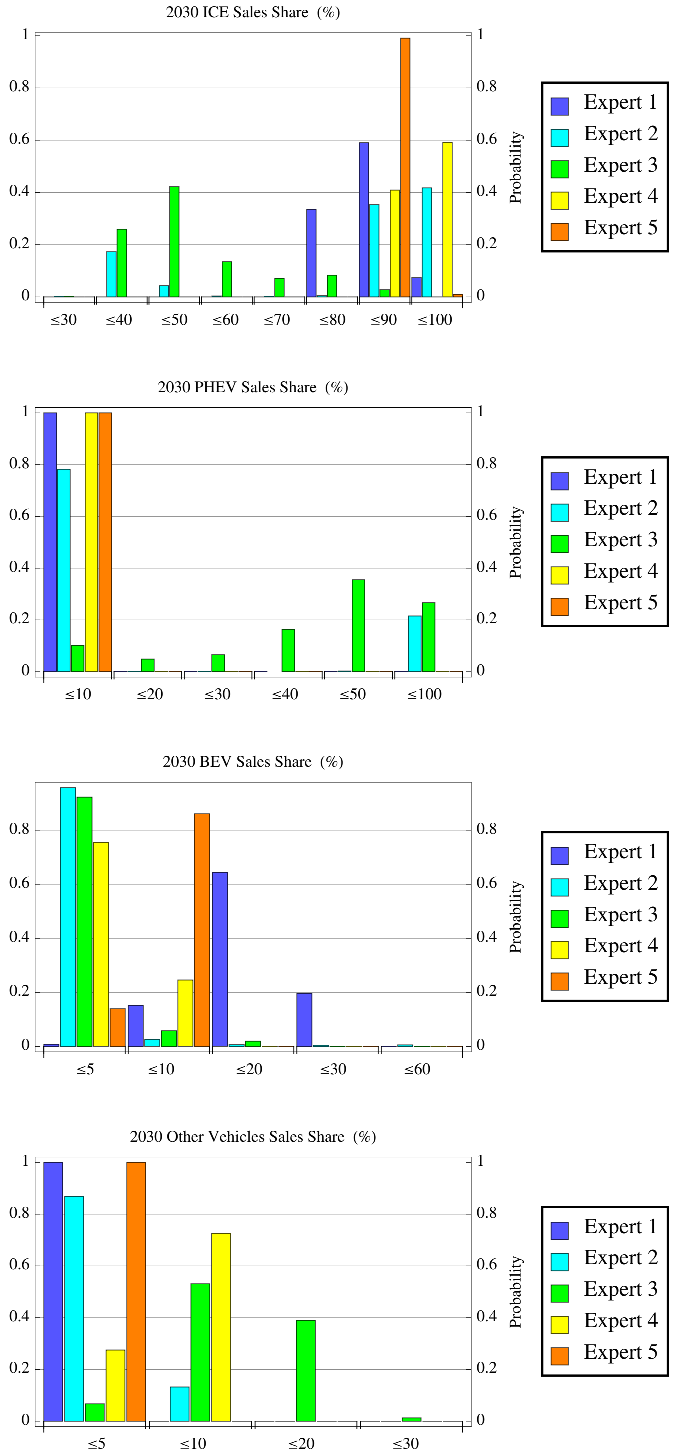


Figure 4.33: BASE 2030 Vehicle Type Sales Shares

Probability distributions of 2030 ICE, PHEV, BEV, and other vehicles' sales shares for experts 1 throughout 5 as derived from their respective BBN under the BASE scenario. For all vehicle types, the lower boundary of the smallest category is zero. All other category boundaries are as indicated on the x-axis of the respective panels. Remark that the absolute upper boundaries do not coincide for all vehicles types.

fleet. No BBN assigns significant probabilities to BEV sales shares higher than 30% in 2030.

Finally, other vehicles (fourth panel in Figure 4.33) have been included in the BBN as a catch-all variable for vehicles which are neither ICE, PHEV, nor BEV. As for BEV, most probability mass is placed in the lowest category of 0 to 5%, to which three experts' BBN (experts 1, 2 and 5) assign 80 to 100% of probability. The second category of 5 to 10% is most likely within the BBN of experts 3 and 4 which attribute weights of 50 and 70%. Expert 3 is the only one to consider higher sales shares for other vehicles; his BBN gives a weight of 40% to a share of 10 to 20%.

Overall, under the BASE scenario, ICE are likely to dominate in the 2030 new vehicle fleet. Most experts' BBN focus on ICE sales shares of 80 to 100%, but some place important weight on lower shares (e.g., 30 to 50%). For PHEV, BEV and other vehicles, modest 2030 sales shares of 0 to 10% for each are very likely as suggested by most of the BBN. Again, single experts' BBN leave room for significantly higher shares, especially for PHEV, where two experts' BBN result in a more than 20% weight on sales shares of more than 50%.

As sales shares are modeled in the BBN to depend on annual user cost differences between the vehicle types, as well as on vehicle range in the case of BEV, the probability distributions for these variables will be presented in the next two paragraphs.

4.5.3.4 BASE Annual User Cost Differences

In the BBN, 2030 sales shares of PHEV and BEV depend on the annual user costs difference such a vehicle causes as compared to a 2030 ICE. Incremental user costs are calculated within the BBN from an expert's assessment of purchase cost differences, battery costs for PHEV and BEV, the vehicle's fuel or electric energy consumption, and fuel and energy prices. It is of interest to relate experts' assessments of vehicle types' cost increments to their judgement of sales shares discussed in the previous paragraph.

Figure 4.34 displays expert assessments of annual user cost differences of PHEV and BEV compared to ICE. In order to keep the size of conditional probability tables for the sales share nodes small enough for elicitation, the number of states for cost differences had to be restricted to a minimum. Thus, a rather coarse picture results, which gives a rough orientation on vehicle cost development expectations.

The BBN of all five experts who have given an estimate produce the result that PHEV user cost differences to ICE (first panel in Figure 4.34) are most likely to be in the range of 0 to 2000 €$_{2008}$ annually. Experts accord probabil-

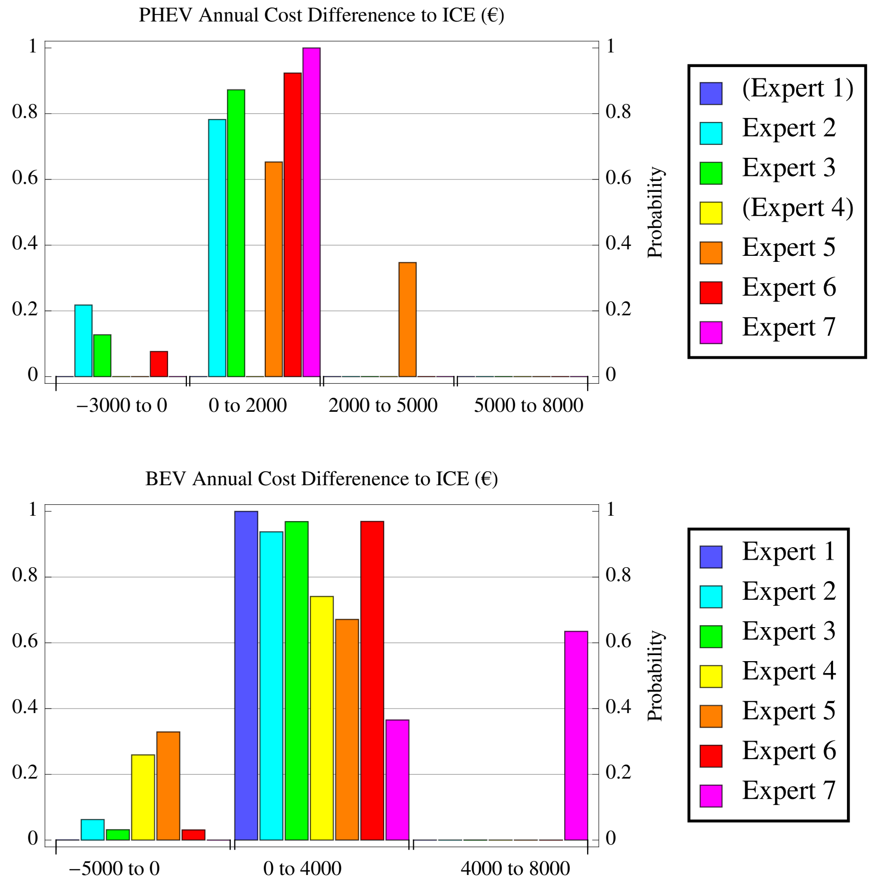


Figure 4.34: BASE 2030 Annual User Cost Differences to ICE
Probability distributions of 2030 PHEV and BEV user cost differences to ICE for experts 1 throughout 5 as derived from their respective BBN under the BASE scenario. Cost differences relate to the annual incremental cost a user incurs for owning and driving a PHEV or BEV instead of an ICE in 2030. All costs are given in €$_{2008}$. Category boundaries differ for the two vehicle types.

ities between 60 and 100% to the variable being in this state under the BASE scenario. Three BBN (those of experts 2, 3 and 6) assign 10 to 20% of weight to the possibility that annual costs for a PHEV are lower than those for an ICE, i.e., in the range of −3000 to 0 €$_{2008}$. One BBN (that of expert 5) attaches 30% of weight to the option that PHEV incremental costs may be higher, namely 2000 to 5000 €$_{2008}$ above annual expenses for an ICE.

For BEV user cost differences (second panel in Figure 4.34), a similar picture arises though categories are even wider. All seven BBN propose that driving a BEV in 2030 is very likely to be more expensive then driving an ICE. Six of them put more than 60% of weight on BEV excess costs of 0 to 4000 €$_{2008}$ per year, and the BBN of expert 7 assigns 60% to the category of 4000 to 8000 €$_{2008}$

on top of the costs of an ICE. Five experts' BBN (experts 2 throughout 6) do not rule out the possibility of BEV user costs being lower than ICE user costs. Two of them assign weights of more than 20% to user cost differences of −5000 to 0 €$_{2008}$, annually.

Summing up, BBN outcomes propose that it is very likely that annual user costs for 2030 PHEV and BEV will be higher than those for ICE. This explains to a large degree why sales shares estimates are as presented in the previous section – much likelihood for dominant ICE shares of 80 to 100%, and small chances for BEV and PHEV to make up for more than 10%, each.

As described above, categories had to be cut very coarsely in order to cover the range of possibilities and keep the elicitation of conditional probabilities feasible, at the same time. However, this approach may hamper the accuracy of results. As it is, experts were asked, e.g, what share of BEV would be sold in 2030 if their annual costs were 0 to 4000 €$_{2008}$ higher than those of ICE. The answer to this sort of question is very likely to differ for annual cost differences of 5 €$_{2008}$ or 3900 €$_{2008}$. Thus, the answer an expert gives may vary strongly, depending on what part of the interval an expert thinks of: the whole interval, its mean, an upper or lower quantile? Results would be more exact and reliable if it had been possible to subdivide the annual cost difference intervals.

4.5.3.5 BASE Electric Ranges

In the BBN, electric range is defined as the distance a vehicle can travel on one complete charge of its battery without using additional energy. PHEV and BEV electric ranges are calculated from battery energy and energy consumption for the respective vehicle type, both specified by the experts. For BEV, range has been modeled as a parent variable of their sales share. For PHEV, electric range has not been assumed to have an impact on consumer choice. With the range in ICE mode added, overall PHEV range is unlikely to be a limiting factor for consumer acceptance. Still, in this paragraph, electric ranges of PHEV are displayed alongside with BEV ranges, because they offer an insight into experts' imagination of PHEV characteristics.

The first panel in Figure 4.35 shows the probability distributions for 2030 PHEV electric range under the BASE scenario. The three categories of 15 to 50, 50 to 100, and 100 to 200 km all gain substantial weight from different experts' BBN. While the lowest of these categories obtains slightly more probability weight than the others, no category is clearly the most likely within all BBN. The category of 200 to nearly 600 km receives zero probability from all but one expert's BBN, which attributes roughly a 15% chance (expert 6).

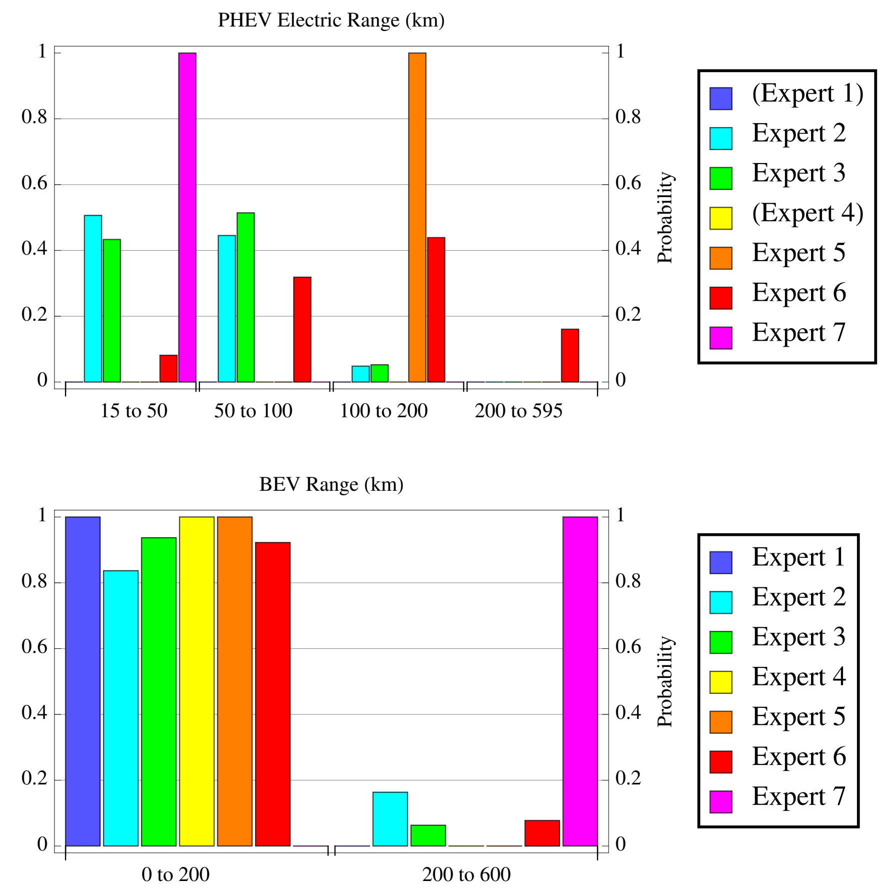


Figure 4.35: BASE 2030 Electric Ranges of PHEV and BEV
Probability distributions of 2030 PHEV and BEV electric ranges with one charge of the battery for all experts as derived from their respective BBN under the BASE scenario. PHEV Electric Range (first panel): For two experts, PHEV range assessments are narrower than the category boundaries displayed: Expert 5 expects it to be 150 to 200 km, expert 7 said it will be 50 km. BEV Range (second panel): Three experts use category boundaries different from those indicated on the x-axis: Expert 1 said 2030 BEV range was 100 km, expert 2 used the categories 25 to 200 and 200 to 500 km, and expert 5 assessed BEV range to be 100 to 150 km.

The range of 2030 BEV is displayed in the second panel of Figure 4.35. All but one BBN give probabilities of 80 to 100% to ranges of 0 to 200 km. Within this category, two BBN yield narrow ranges of 100 km (expert 1) and 100 to 150 km (expert 5), respectively. Four experts' BBN give positive probabilities to larger ranges of 200 to 600 km; one of them (that of expert 7) attributes a full 100% of probability to a range in this category.

In summary, the distribution for PHEV ranges looks more widespread than that for BEV, but this is predominantly caused by the fact that PHEV ranges are subdivided into more categories, which could not be done for BEV because it would have hampered elicitation. Thus, for both PHEV and BEV, experts' BBN put the bulk of probability onto electric ranges of up to 200 km. Still, for BEV, four BBN leave room for ranges much larger than 200 km, while only one does so for PHEV. Moreover, one BBN shows that such a large range will be reached for BEV under the BASE scenario.

4.5.4 Comparison of Outcomes under the different Scenarios

In the previous section, results from running the experts' BBN under the BASE scenario have been presented in detail. The aim of this section is to get an overview of what are the most important changes under the different alternative scenarios. Scenario effects on three groups of variables will be discussed, namely on 2030 new car fleet emissions, vehicle costs, and sales shares of the different vehicle types.

4.5.4.1 2030 German New Car Fleet CO_2 Emissions

One of the central research questions the BBN has been designed to examine is how CO_2 emissions from vehicles will develop under different conditions. Outcomes from running the BBN under different scenarios can be compared in regard to the resulting CO_2 emissions of the 2030 German new vehicle fleet. To get a detailed overview of the experts' assessments, probability distributions on emissions as shown in Figure 4.31 for the BASE 2030 new vehicle fleet and in Figure 4.32 for the single car types under BASE could be compared for all scenarios. However, as much information is conveyed by this approach, it is unlikely that a clear picture would result from such a comparison. Instead, in a first step, expected values of fleet emissions derived from the different BBN will be compared. This is helpful for giving an impression of the effect of different scenarios: Which of them are suitable for reducing emissions compared to the BASE state? Are there scenarios under which 2030 new fleet emissions will increase?

Once candidate scenarios for CO_2 emission reduction have been identified, they can be analyzed in more detail. At that stage, experts' uncertainty on the actual outcome, which can not be seen from the expected values, can be brought in for the candidate scenarios.

For each of the scenarios analyzed, Figure 4.36 displays the range of expected values for 2030 German new vehicle fleet emissions over all experts' BBN. A description of the scenarios has been given in Section 4.5.1. For each scenario, the median expert assessment is marked in order to offer an impression of whether expert assessments concentrate in a part of the range or are spread relatively evenly. For most of the scenarios, the ranges represent the expected values for the BBN of the five experts who have specified 2030 sales share distributions (i.e., experts 1 throughout 5). For the scenario of a stricter European car CO_2 emission limit (Cpol), the bar includes the assessments from three experts' BBN only, because two more experts (experts 1 and 4) have framed 2030 ICE fuel consumption independently of EU regulation.[20]

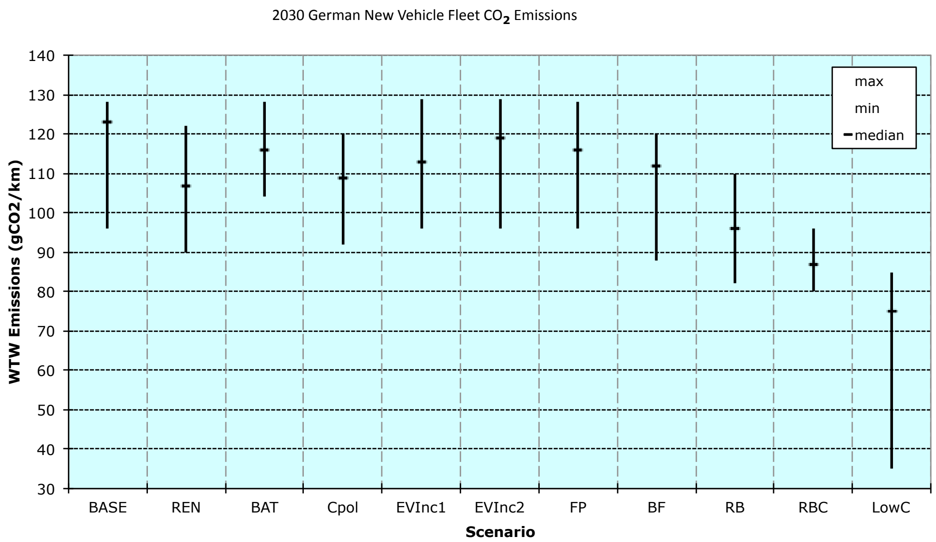


Figure 4.36: 2030 German New Vehicle Fleet CO_2 Emissions under different Scenarios (Expected Values)
For each scenario, the range of expected values of WTW CO_2 emissions over all experts is represented as a bar (minimum to maximum value given by any expert) with the median assessment marked by a dot. Each bar relates to the expected values of expert 1 throughout 5, except for the Cpol scenario, where experts 1 and 4 did not offer an assessment.

The first eight scenarios in Figure 4.36 are the baseline scenario (BASE) and the seven elementary scenarios derived from it, assuming a higher quota of renewable energy in the 2030 electricity mix (REN), favorable battery development (BAT), a stricter EU car CO_2 emission policy (Cpol), consumer incentives for buying PHEV or BEV (EVInc1 and EVInc2), higher fuel prices (FP), or a

[20]Expert 1 said that 2030 ICE fuel consumption did not depend on European regulation, but would be driven by global competition. Expert 4 pointed out that the EU regulation was already settled such that there were no different options. He based his assessment on a regulation between those considered for the BASE and Cpol scenario. For more details, see Section 4.4.3.1.

higher share of biofuels in the 2030 fuel mix (BF). Parameters for the scenarios have been listed in Table 4.10.

As represented by the first bar, under the BASE scenario, the expected values for 2030 new vehicle fleet emissions range from 96 to 128 gCO_2/km, and the majority of BBN yields values of more than 120 gCO_2/km. Comparing the bars for the different scenarios, it can be seen that some scenarios do not move the range of expected emissions downwards. Apparently, consumer incentives for buying PHEV and BEV as modeled in scenarios EVInc1 and EVInc2 do not alter the position or length of the bar significantly, nor does the scenario for a higher fuel price (FP). However, for all three, the median expected value is lower than in the BASE scenario (between 110 and 120 gCO_2/km). The BAT scenario, which assumes a favorable development of battery energy densities and prices, even leads to 2030 expected new fleet emissions in an upper subrange of BASE expected values, i.e., 104 to 128 gCO_2/km. The three remaining basic scenarios, REN, Cpol and BF, are candidates for possible fleet emission reductions. The ranges of expected values are 90 to 122 gCO_2/km under REN, 92 to 120 gCO_2/km under Cpol, and 88 to 120 gCO_2/km under the BF scenario. Median assessments are around 110 gCO_2/km for all three scenarios. Thus, both the lower and higher boundary of expected values derived from the different experts' BBN as well as the median assessment are lower than under the BASE scenario, which makes these scenarios suitable candidates for reducing emissions. However, only a modest reduction in the range of 10 gCO_2/km or less is brought about.

Figure 4.36 also contains the results from running combined scenarios with the aim of further emission reduction. The ninth column, labelled 'RB', shows expected values for 2030 new car fleet emissions under a combined REN and BF scenario, and the tenth, 'RBC', shows the outcome if Cpol is added, on top. Combining renewable energies and biofuels brings down the range of expected values by approximately another 10 gCO_2/km compared to any of the measures REN, BF or Cpol alone, leaving it at 82 to 110 gCO_2/km. However, only when adding a stricter EU car CO_2 emission policy to the three networks where this is possible (the BBN of experts 2, 3 and 5), the range of assessments is narrowed down substantially (to 80 to 96 gCO_2/km, median 87 gCO_2/km), and fleet CO_2 emissions below 100 gCO_2 km are a common expectation within all experts' BBN.

Finally, in its last column, the figure shows the results from running the BBN in a bottom-up manner, enforcing the lowest fleet emissions technically possible. As can be seen, this 'LowC' scenario leads to a range of expected 2030 fleet emissions that starts from 35 and ends at 85 gCO_2/km. This scenario will also be described later in this section.

Reducing Car CO_2 Emissions: Cpol, REN, BF, and a combined Scenario

As Figure 4.36 has indicated, there is no coinciding answer to the question what scenario reduces emissions most effectively, and there is no basic scenario under which all experts' BBN yield a strong emission reduction. Table 4.11 quantifies the expected fleet CO_2 emissions for five experts' BBN under the BASE, REN, Cpol und BF scenarios. In the second half of the table, it is listed under which scenario the respective BBN produces the strongest reduction of emissions, along with its absolute and relative size compared to BASE. Two BBN show that Cpol would have the strongest impact, while within two further BBN, this scenario is either not feasible or does not make a difference at all. Two BBN focus on the BF scenario, and one favors the REN scenario. Expected emission reductions range from 8 to 31 gCO_2/km, which is an 8 to 25% reduction compared to the BASE emissions within the respective BBN.

Table 4.11: The Effect of Emission Reducing Scenarios

	Expected Values[1]				Strongest Reduction[2]		
	BASE	REN	Cpol	BF	Scen.	Abs.	Rel.
Exp. 1	96	90		88	BF	−8g	−8%
Exp. 2	123	117	92	112	Cpol	−31g	−25%
Exp. 3	128	104	120	120	REN	−24g	−19%
Exp. 4	109	107		98	BF	−11g	0%
Exp. 5	128	122	109	116	Cpol	−19g	−15%

[1]Expected values for WTW 2030 German new vehicle fleet CO_2 emissions (gCO_2/km) under four scenarios.

[2]Strongest reduction in the expected value for 2030 German new vehicle fleet emissions, compared to the BASE scenario; Scen.: Scenario where strongest reduction occurs; Abs.: CO_2 emission reduction in absolute terms (gCO_2/km); Rel.: relative CO_2 emission reduction as a share of BASE emissions.

Consequently, for a policy-maker who wants to reduce car CO_2 emissions and who puts some trust into the expertise of each of these experts, there is no single measure that can guarantee the intended effect. As the assessments do not coincide, there is uncertainty on the outcomes of the different measures.

A possible solution to this problem can be to combine different measures. Such an approach may result in a robust (but potentially costly) reduction of CO_2 emissions. In order to judge the emission effect of combinations of measures, the BBN have been run using different combinations, and the resulting 2030 new vehicle fleet emissions have been included in Figure 4.36. It has been shown that a combined REN and BF scenario yields a decrease in expected CO_2 emissions compared to the effect of each measure, individually. When extending the combined scenario to include Cpol, as well, BBN results converge to a narrower, lower emission range. Thus, the RBC scenario, combining three different measures, is a robust approach for bringing down fleet CO_2 emissions.

So far, only expected values for emissions under the different scenarios have been discussed, while the BBN contain complete distributions. To show that there still is uncertainty about the conclusions just drawn, caused by the question of whether expected values will actually be met, and in order to give an impression of the degree of uncertainty, more detailed graphics are provided for the scenarios REN, Cpol, BF, the combined RBC scenario, and for BASE (for comparison). Figure 4.37 shows the expected values the single BBN assign to 2030 new vehicle fleet CO_2 emissions under the different scenarios along with error bars which represent one standard deviation (sd) for the respective expert and scenario. The bars are not to be confused with those shown in Figure 4.36, which aggregated the different experts' judgements. In Figure 4.37, each error bar depicts the assessment derived from just one expert's BBN, with the point in the middle representing the respective expected value. For each expert, a different color has been used, and for traceability, the colors have been assigned in the same way as in the description of elicitation results in Section 4.4.3 and the presentation of BASE outcomes in Section 4.5.3. When there is no bar but just a point, the expert did not express any uncertainty. Along with fleet emissions, the emissions of the different vehicle types, ICE, PHEV and BEV, are shown in order to give a more complete picture of how fleet emissions result. This also allows to include the CO_2 emission estimates for the single car types derived from the BBN of experts 6 and 7, which do not produce fleet estimates.

The first panel in Figure 4.37 shows the expected values and one sd intervals for 2030 new vehicle emissions under the **BASE** scenario. For comparison, the complete distributions have been presented in Figures 4.31 and 4.32 in the previous section. It can be seen that for fleet emissions, the range covering the expected value with one sd over all BBN is roughly 80 to 140 gCO_2/km, with two BBN proposing bars in the lower half of this interval, and three in the upper half. The one sd ranges of single experts' BBN span 35 gCO_2/km, at most. For ICE, the overall range is similar (80 to 150 gCO_2/km), but ranges of single assessments are up to 50 gCO_2/km. This shows that some experts are more uncertain in regard to the exact value of 2030 new ICE emissions than concerning overall fleet emissions. For PHEV and BEV, the picture gets

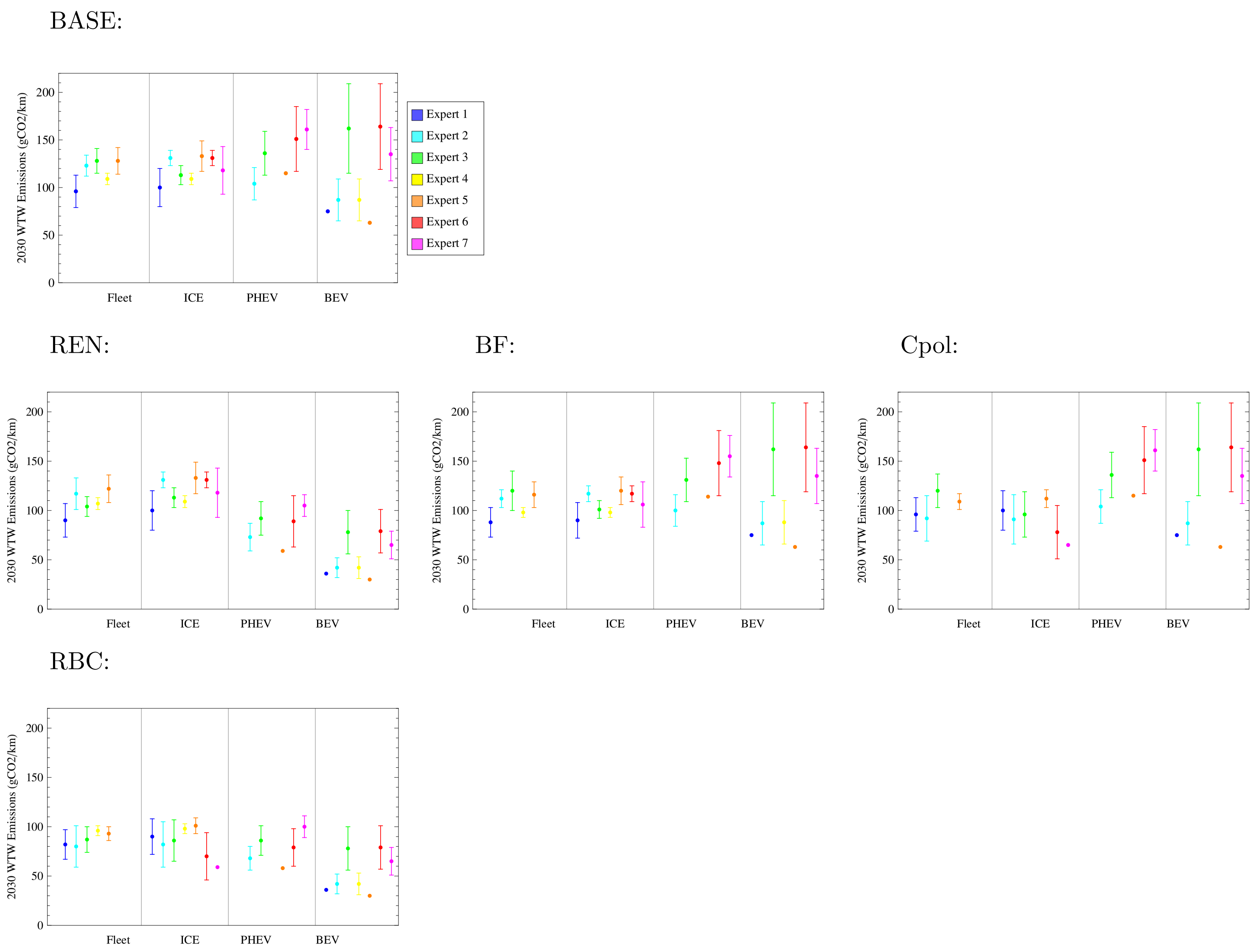


Figure 4.37: 2030 German New Vehicle Fleet and Car Type CO_2 Emissions under different Scenarios (Error Bars)
The figure shows expected values for 2030 German new vehicle CO_2 emissions (WTW) with error bars in the range of one standard deviation. For fleet emissions, assessments of experts 1 throughout 5 are shown; car type emissions are presented for all seven experts.

increasingly divergent. For most experts' BBN, the ranges of one sd increase, but one (in the case of PHEV) or two (in the case of BEV) give point estimates with zero sd. Moreover, the range of assessments over all BBN grows to between 85 and 185 gCO_2/km for PHEV and further to between 60 and 210 gCO_2/km for BEV. For the latter, experts' BBN fall into two groups one of which shows that BEV are expected to be relatively low-emitting vehicles (up to 110 gCO_2/km), and one of which results in BEV emissions which may well be much higher than those of ICE or the overall fleet. Apparently, experts' assessments coincide much better for ICE than for PHEV and BEV. A reason may be that for the latter two vehicle types, no common picture exists of what they will look like and what will be their standard application.

In the second panel of Figure 4.37, the effect of the **REN** scenario can be seen, which introduces more renewable energy into the electricity mix. Unsurprisingly, for ICE nothing changes in comparison to the BASE scenario. For PHEV and BEV, emission ranges shift downwards considerably. PHEV expectations with one sd cover the range of 60 to 115 gCO_2/km. For BEV, they cover 30 to 100 gCO_2/km, with the assessments from four experts' BBN placed in the subrange of 30 to 50 gCO_2/km. For most BBN, the span of one sd for BEV emissions has decreased strongly compared to the BASE scenario. However, for the overall fleet, the range of assessments is similar to that under the BASE scenario. For most BBN, the expected value has moved only slightly downwards, and the range of one sd has barely changed. The maximum downward shift is more than 20 gCO_2/km, derived from the BBN of expert 3. The small effect of the REN scenario on fleet emissions in most BBN is due to the high sales shares most experts accord to ICE, emissions of which remain unaffected under REN. As the increase of renewable electricity has been modeled not to change any of the variables influencing sales shares (e.g., the electricity price), the REN scenario does not change the new fleet composition compared to BASE. Thus, BASE sales share distributions as presented in Figure 4.33 also apply under the REN scenario, such that expected values for ICE sales shares remain at 80 to 90% for four out of five experts' BBN. Sales shares under the different scenarios will be discussed in Section 4.5.4.3, and their expected values will be shown in Figure 4.42.

The third panel of Figure 4.37 shows the impact of the **BF** scenario which increases the share of biofuels in the 2030 fuel mix. Complementary to the REN scenario just described, this measure affects ICE most strongly and has some impact on PHEV, but none on BEV. Consequently, for BEV, there is no change compared to the BASE case. For ICE emissions, for all experts' BBN, there is a downward shift of 10 to 14 gCO_2/km, leading to 2030 new ICE emission expected values of 70 to 135 gCO/km. The size of one sd ranges has barely changed. For PHEV, changes in the expected values are -1 to -6 gCO_2/km compared to the BASE scenario, which is barely visible in the figure. The small effect on PHEV is due to the fact that all experts set their expected electric range to at least 50 km[21], which is enough to cover the distance driven in a day by 70% of car drivers. Thus, on a given day, only 30% of average car drivers would make use of the combustion engine mode when driving a PHEV and starting with a fully charged battery, as is assumed in the present analysis. This is the reason for the limited impact of fuel carbon content on PHEV emissions. Again, one sd interval sizes are nearly unchanged. The BF effect on overall fleet emissions is a reduction in the expected values of a magnitude of 8 to 12 gCO_2/km. This is a bit less than for ICE, which contribute a very large share of 2030 new vehicle sales according to most experts' BBN. As for REN, the BF scenario does not affect the sales share distributions, because the introduction of more biofuels into the 2030 fuel mix has been assumed to be neutral in regard to fuel prices.

The result of a stricter EU car CO_2 emission limit as modeled in the **Cpol** scenario is depicted in the fourth panel of Figure 4.37. Remind that the Cpol scenario can not be run in the BBN of experts 1 and 4. Expert 1 said that European policy had no impact, such that for him, the error bars are as under the BASE scenario. Expert 4 said that the EU regulation was already decided upon and that there would be no different regulation. For him, no assessment under the Cpol scenario is available, and thus no error bars are included in the figure. The Cpol scenario tightens the ICE emission limit compared to the BASE scenario (from 115 gCO_2 TTW to 95 gCO_2 WTW), but does not change the PHEV emission limit, which remains at 115 gCO_2/km TTW, nor does it introduce a limit for BEV. As a result, the measure affects ICE emissions, only. Expected values for ICE emissions shift downwards within five experts' BBN by as much as 17 to 53 gCO_2/km. The highest reduction of 53 gCO_2/km occurs in the BBN of two experts, namely the two who have not provided any sales shares. Thus, the overall fleet effect of the measure can not be discussed for them, but can be assumed to be of important size. Standard deviation changes show no uniform pattern; they are positive within some BBN and negative for others. The three BBN of experts who have provided fleet estimates and have specified an impact of a stricter carbon policy all show that it reduces fleet emissions. Reductions in the expected fleet CO_2 emission value range from 8 to 31 gCO_2/km. The Cpol scenario leaves the 2030 new vehicle fleet composition unaffected for all but one expert (expert 2). In his BBN, Cpol

[21]For more details, see Table 4.17 and the description in Section 4.5.4.4.

leads to an increase of the ICE sales share by 10%, displacing PHEV. This is caused by an increase in annual excess costs of PHEV compared to ICE. ICE are more attractive under this scenario because the stricter policy triggers a reduction in their fuel consumption, and the related additional purchase costs are overcompensated by the decrease in fuel expenditures.

Finally, the last panel of Figure 4.37 shows the effect of the three measures (more renewables, more biofuels, and a stricter emission limit) combined, called the **RBC** scenario. At first glance, it can be seen that a rather unified picture results compared to all other panels. Expected values of emissions are 100 gCO_2/km at most over all BBN and all vehicle types. No error bar surpasses emissions of 110 gCO_2/km. Assessments are most uniform for fleet emissions (expected values of 80 to 96 gCO_2/km, and an overall one sd range from 60 to 100 gCO_2/km), and diverge most for BEV emissions, where four experts' BBN yield very low emissions in the range of 30 to 50 gCO_2/km, and three more result in higher emissions of 50 to 100 gCO_2/km (one sd ranges). As no assessment of fleet emissions including one sd surpasses 100 gCO_2/km, this combination of measures can be seen as a relatively robust solution for reducing 2030 new fleet emissions nearly by half as compared to 2008 new fleet emissions.

As ICE are accorded very high market shares of more than 80% within four of five BBN under the Cpol scenario, combining BF and Cpol would suffice for bringing down fleet emissions in these networks. However, a fifth BBN (that of expert 3) assigns a market share of 40% to PHEV under the Cpol, REN and BF scenarios. Following results from this BBN, the expected value of emissions when combining Cpol and BF only is 113 gCO_2/km, and the sd is 16 gCO_2/km. Thus, whether all three measures are needed depends on the trust decision-makers put into the assessments of the single experts.

The Impact of Energy Carbon Content

In the current public debate, BEV are often treated as low-emission vehicles. Although, due to their minor market shares in most BBN[22], no major fleet emission reductions can be achieved through PHEV and BEV under the scenarios discussed so far, these scenarios can be used to discuss the preconditions for PHEV and BEV to emit little CO_2. As seen from Figure 4.37 (first panel), under BASE conditions, PHEV and BEV can be expected to emit less CO_2 than ICE only within roughly half of the BBN. From the complete probability distributions for vehicle type CO_2 emissions under the BASE scenario, discussed

[22] For a detailed discussion of sales shares under the different scenarios, see Section 4.5.4.3, and for a presentation of their expected values, Figure 4.42.

in Section 4.5.3.2 and shown in Figure 4.32, it can be seen that three experts' BBN (those of experts 3, 6 and 7) place more probability mass on higher emission categories for PHEV or BEV than for ICE. Within some of the remaining BBN, probability mass is widespread enough to allow for 2030 PHEV and BEV emissions to be at least as high as ICE emissions.

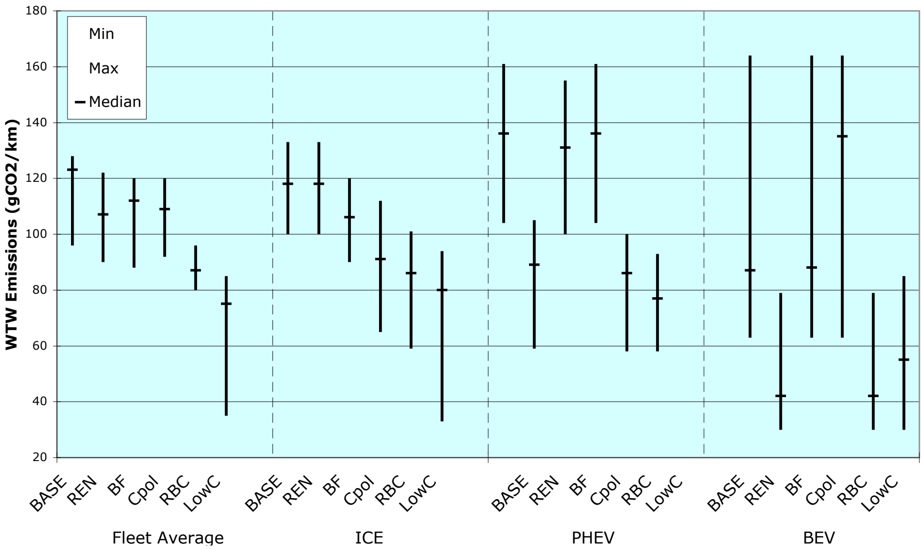


Figure 4.38: 2030 German New Vehicle Fleet and Car Type CO_2 Emissions under six Scenarios (Expected Values)

For each car type and scenario, the range of expected values over the experts is represented as a bar (minimum to maximum value given by any expert) with the median assessment marked by a dot. For most scenarios, bars relate to the expected values of expert 1 throughout 5 for fleet averages, experts 1 throughout 7 for ICE and BEV, and experts 2, 3, 5, 6 and 7 for PHEV. For Cpol, they do not include judgements from experts 1 and 4.

To give a simplified summary of the different assessments, Figure 4.38 displays the range of expected CO_2 emissions over all experts' BBN in the same style as used in Figure 4.36, i.e., without considering the uncertainty experts have expressed. Differently from the figure presented earlier, less scenarios are represented, but the present figure includes 2030 CO_2 emission expectations for the fleet average and the distinct car types. For the BASE scenario, it can be seen that expected values for ICE emissions span a range from roughly 100 to 130 gCO_2/km. PHEV expected emissions reach higher than those for ICE (up to 160 gCO_2/km), and their lower boundary is slightly higher than for ICE, as well. For BEV, a relatively large range of expected values results, roughly from 60 to 160 gCO_2/km. This is about three times the size of the interval of

ICE expected emissions, and covers the possibility of BEV being relatively low emitting vehicles as well as relatively high emitters. Thus, under the BASE scenario, PHEV and BEV can not generally be considered as low-emission vehicles, but even run the risk of being more emission intensive than ICE in the view of roughly half of the experts.

The picture changes when electricity carbon content is reduced, as has been done under the REN scenario. From Figure 4.38, it can be seen that in this case, PHEV expected values for CO_2 emissions drop to 60 to roughly 100 g/km, and BEV values to about 30 to 80 g/km. As the figure shows, in the alternative scenarios, PHEV expected emissions do not get much lower than under REN. Additional effects of an increased biofuel quota or of the LowC scenario are minor. For BEV, the REN scenario (and the RBC scenario, likewise) triggers the lowest range of expected emissions of all scenarios considered. A look at the more complete picture including standard deviations, presented in Figure 4.37 (second panel), confirms the impression that under REN, experts' BBN yield PHEV and BEV emissions lower than ICE emissions. Still, for PHEV, the one sd ranges include values of more than 100 gCO_2/km for three out of five experts' BBN and even for BEV, intervals derived from two experts' BBN touch this value at their upper boundary. In sum, REN clearly reduces PHEV and BEV emissions and makes them relatively low-emitting vehicles, compared to ICE. However, it does not necessarily make them extremely low carbon emitters in absolute terms. Only four out of seven experts' BBN yield expected BEV emissions with one sd within the interval of roughly 30 to 50 gCO_2/km, and no assessment of PHEV emissions reaches such a low level.

The Low CO_2 Emission Scenario (LowC)

In the previous paragraph, the effects of different measures for driving down car CO_2 emissions were analyzed in a 'top-down' manner: Parameters for a stricter CO_2 policy or for decreased fuel and electric energy carbon contents were entered into the respective nodes of the experts' BBN, which then were run to determine the resulting new vehicle fleet CO_2 emissions. In contrast, in this paragraph a 'bottom up' approach is chosen: The fleet CO_2 emission node is set to its lowest possible state, and it is left to the BBN to determine what is the most probable combination of other nodes' states to have caused this outcome. Apart from the fleet emission node, no other node is instantiated. This can only be done for the five BBN containing fleet emission nodes, i.e., the BBN of experts 1 throughout 5.

For each BBN, the lowest possible fleet emissions have been chosen individually. As no minimization routine is offered by the software, this has been done manually. Each BBN's fleet emission node has been instantiated at the state '90 to 100 gCO_2/km WTW' and run. Then, the emission corridor has been moved downwards in 10 g steps until the sampling update mechnism delivered error messages because samples were rejected. A BBN's lowest possible fleet emission is defined as the lowest 10 g interval for which the BBN still runs smoothly. Lowest possible WTW fleet emissions diverge strongly for the different experts' BBN. In that of expert 1, they are 30 to 40 gCO_2/km, for expert 2, 50 to 60 g, for expert 3, 70 to 80 g, and for experts 4 and 5, minimum feasible fleet emissions are 80 to 90 gCO_2/km.

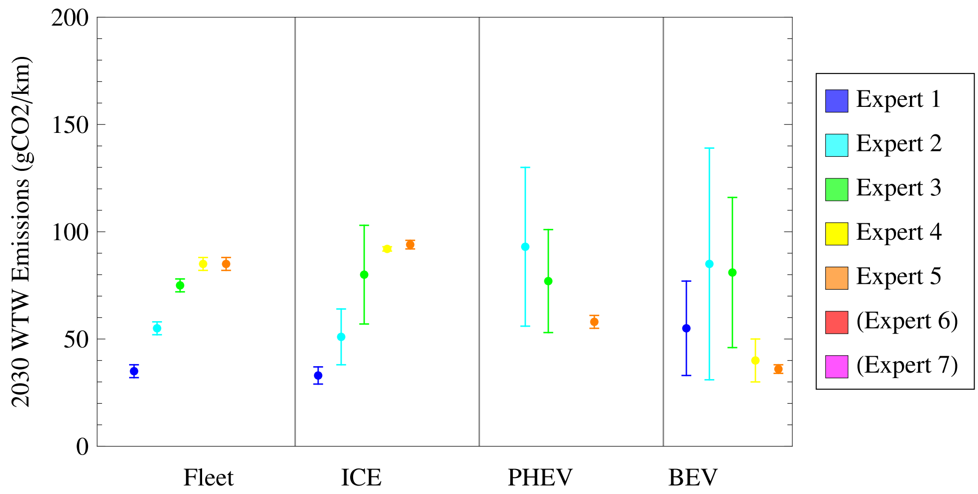


Figure 4.39: 2030 German New Vehicle Fleet and Car Type CO_2 Emissions under the LowC Scenario (Error Bars)
The figure shows the experts' expected values for 2030 German new vehicle fleet and car type CO_2 emissions (WTW) under the LowC scenario with error bars of one standard deviation. The LowC scenario could be run in the BBN of experts 1 throughout 5.

Figure 4.39 shows the expected values for fleet and car type emissions under the LowC scenario with error bars spanning one standard deviation. Not astonishingly, error bars for fleet emissions are very small, as 2030 fleet emissions have been set to a corridor of 10 gCO_2/km for each expert. For some BBN, the standard deviations of single car type emissions are much larger.[23]

As the figure shows, two of the five BBN (those of experts 1 and 2) produce 2030 new PHEV or BEV emissions higher than ICE emissions under the LowC

[23]The approximate inference function used for compiling the networks draws samples from the distributions underlying the nodes. As the corridor for fleet emissions has been predetermined, samples must represent this prerequisite. Thus, single vehicle type emissions of a sample always combine such that their average (weighted with car types' sales shares) falls into the range of allowed fleet emissions.

scenario. Within the BBN of expert 3 they are similar, with the PHEV expected value and error bar placed slightly lower (roughly 5 g) than that for ICE, and the BEV standard deviation larger than that for the other two car types. The remaining two BBN (those of experts 4 and 5) suggest that PHEV and BEV will emit considerably less. This holds especially for BEV, expected emissions of which are around 40 gCO_2/km within both BBN under the LowC scenario, which is less than half the expected ICE emissions. Within these two BBN, PHEV or BEV are indispensable for bringing down fleet emissions to their lowest possible level, as ICE emissions lie above LowC average fleet emissions.

Market share expected values for all scenarios are represented in Figure 4.42, as they will be discussed in detail in a separate section. For the LowC scenario, most experts' BBN yield dominant ICE shares of 70% (expert 2), or above 80% (experts 1, 4 and 5). However, LowC is one of the few scenarios which, according to one BBN (that of expert 3), could lead to a dominance of PHEV in the 2030 German new vehicle fleet. The network assigns an expected market share of 50% to PHEV, and only 39% to ICE under these conditions. A second BBN (that of expert 2) shows an increase in PHEV expected market share by 6 percentage points to 23% compared to the PHEV share under the BASE scenario. As regards BEV, three experts' BBN result in a duplication of expected market shares under the LowC scenario as compared to BASE, but from very low base values: In the BBN of experts 2 and 3, they rise from 2 to 4%, and in that of expert 4 from 3 to 7%. For two experts (experts 1 and 5), the market shares of the different vehicle types under LowC are hardly different from BASE market shares.

The effect of market share redistributions on fleet CO_2 emissions varies. The allocation of market shares from ICE to PHEV as carried out within the BBN of two experts when moving from the BASE to the LowC scenario is likely to increase fleet emissions in case of expert 2, and leave them unchanged or decrease them minimally in case of expert 3 due to car type emissions discussed above. The replacement of ICE by BEV shares, which takes places within three BBN under LowC compared to BASE, is likely to increase emissions in the case of expert 2, not to make a difference in the case of expert 3, and to strongly decrease emissions in case of expert 4.

An overview of the impact of the LowC scenario can be gained by comparing emissions to those under other scenarios. In Figure 4.40, the LowC error bar chart from Figure 4.39 is shown alongside with the corresponding graphics for the baseline (BASE) and the combined renewables, biofuels and EU CO_2 policy scenario (RBC). All three figures have been displayed before, but are assembled here on one page for easier comparison.

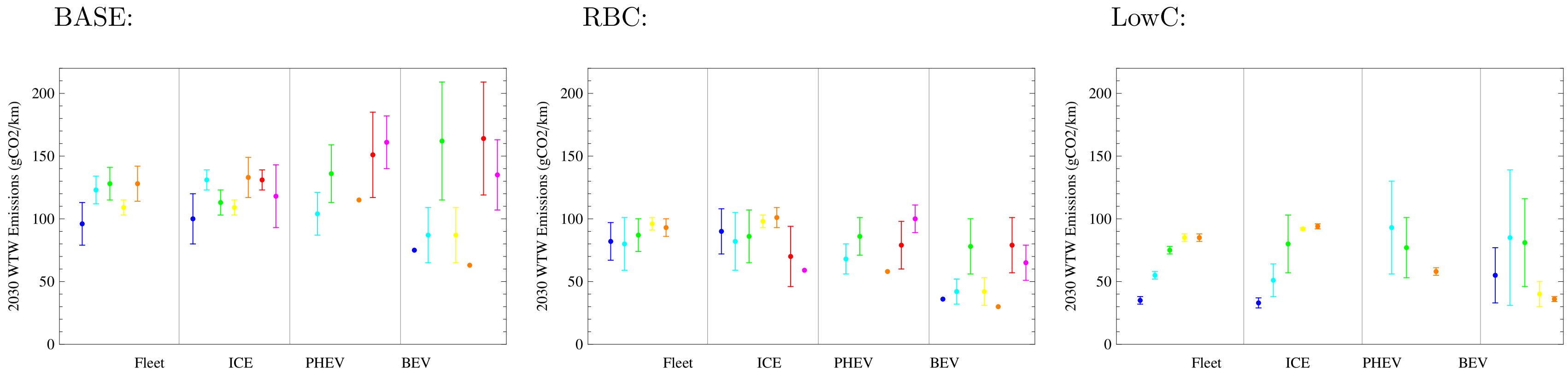


Figure 4.40: 2030 German New Vehicle Fleet and Car Type CO_2 Emissions under the BASE, RBC and LowC Scenario (Error Bars)
The figure shows expected values for 2030 German new vehicle fleet CO_2 emissions (WTW) with error bars in the range of one standard deviation. The same colors are assigned to the experts as before; for a legend, see, e.g., Figure 4.39.

It can be seen that LowC fleet emissions are much lower than BASE fleet emissions in all five experts' BBN. Moreover, for all experts, expected values for LowC fleet emissions are lower than those for RBC. For three of the experts (experts 1, 2 and 4), the LowC one standard deviation error bars are placed entirely below those for BASE and RBC, such that emission assessments for the different scenarios do not overlap. For single experts, reductions of expected fleet emissions by more than 50% (expert 1) and by 30% (expert 2) are achieved in the LowC scenario as compared to the RBC scenario, where emissions are already relatively low in contrast to BASE. For the remaining three experts, relative savings are in the order of magnitude of 5 to 10%.

This shows that it is possible to drive fleet emissions even lower than under the RBC scenario, which combines the lowest carbon intensities of electric energy and fuel mix modeled in the BBN with the strictest EU car CO_2 emission limit considered. To figure out which factors are responsible for the further reduction, a closer look must be taken at the states of further variables under the LowC scenario.

Table 4.12 shows expected values and standard deviations for a number of variables under the BASE, RBC and LowC scenario. The horizontal blocks of three rows refer to one expert, each, and give results from his BBN under the three scenarios. The vertical blocks relate to different variable sets.

The first vertical block displays expectations for fuel and electric energy consumption of the different car types. The second block presents CO_2 contents of fuel and electric energy, and the third one describes car CO_2 emission limits.

For examining combustion engine emissions, i.e., emissions of ICE and of PHEV in combustion engine mode, a look has to be taken at fuel consumption levels and at fuel carbon contents.

Regarding fuel carbon contents, it can be seen that under the LowC scenario, three of the five BBN do not set it to its minimum possible value. The lowest possible level of fuel carbon content implemented in the BBN is 2600 gCO_2 per liter fuel. While the RBC scenario sets carbon intensities of fuel and electricity to the lowest levels, within the LowC scenario, the BBN updating mechanism produces probability distributions for these variables which indicate how likely it is that each possible state is realized. In the BBN of experts 1 throughout 3, the expected values of 2800 gCO_2/l (experts 1 and 3) and 2840 gCO_2/l (expert 2) are closer to BASE fuel carbon content than to minimum possible carbon content. In contrast, for experts 4 and 5 the expected value is 2600 gCO_2 per liter fuel.

As fuel carbon content can not be moved below the RBC level in the BBN, it is necessary to reduce fuel consumption of ICE if they are to emit less than under the RBC scenario. Similarly, PHEV fuel consumption needs to be reduced if they are to emit less in combustion engine mode.

The first and second column in the first block of Table 4.12 list expected values and standard deviations for fuel consumption of 2030 ICE and PHEV. For ICE, it can be seen that LowC expected values for fuel consumption are lower than under the RBC scenario for all five experts.

However, there are huge differences in regard to by how much they decrease: By 65% for expert 1, 44% for expert 2, 12% for expert 3, and 8% for experts 4 and 5.[24] In absolute numbers, expected values for 2030 ICE fuel consumption under the LowC scenario are 1.2, 1.8, 2.9, 3.5 and 3.6 l/100km for experts 1 throughout 5.

This finding complements what has been said on fuel carbon contents: In the BBN where fuel carbon content is relatively high, strong cuts in ICE fuel consumption are realized and relatively low consumption levels are reached in order to achieve low overall carbon emissions (predominantly in the BBN of experts 1 and 2). Where fuel consumption reductions are relatively modest (in the BBN of experts 4 and 5), fuel carbon content comes down to its minimum.

The latter two BBN, where expert assessments are such that ICE fuel consumption can not be brought down below 3.5 l/100km, are also those where LowC fleet emissions remain highest, at 80 to 90 gCO_2/km, as has been shown in Figure 4.39. The BBN of expert 3 is different in that the weight of ICE in the overall fleet is much lower than for the other experts, and PHEV dominate under the LowC scenario. In this case, the pressure on ICE to emit less under the LowC scenario is smaller, resulting in an ICE fuel consumption assessment in-between the two groups just sketched, combined with a relatively high fuel carbon content.

Analogously, PHEV CO_2 emissions in combustion engine mode can be reduced below RBC levels only through decreases in fuel consumption. However, as can be seen from the second column in the first block of Table 4.12, this is the case only in the BBN of expert 3. In his BBN, the expected value of PHEV LowC fuel consumption is 9% (or 0.4 l/100km) lower than under the RBC and BASE scenarios, reaching an absolute consumption of 3.9 l/100km. This is still relatively high, resulting in LowC WTW PHEV emissions of 107 gCO_2/km in combustion engine mode when combined with the relatively high fuel carbon intensity resulting under LowC in the same BBN. The reason why average PHEV emissions are much lower is that expert 3's BBN yields a large electric driving

[24]There are also large differences regarding fuel consumption reduction under RBC as compared to BASE, where there is no change in the BBN of experts 1 and 4, a decrease by 29% for expert 2, and 15% decreases for experts 3 and 5.

Table 4.12: Parameters under BASE, RBC, and LowC

(Table continued on next page)

Scen_Exp	ICE fcons	PHEV fcons	PHEV elcons	BEV elcons	fuel C.int	ener. C.int	ICE C.lim	PHEV C.lim
BASE_1	3.5			12	(2900)[1]	(625)		
	±0.7			±0				
RBC_1	3.5			12	(2600)	(300)		
	±0.7			±0				
LowC_1	1.2			15	2800	385		
	±0.1			±4	±200	±170		
BASE_2	4.5	3.6	17	14	(2900)	(625)	(115TTW)	(115TTW)
	±0.3	±0.4	±4	±4				
RBC_2	3.2	3.6	17	14	(2600)	(300)	(95WTW)	(115TTW)
	±0.9	±0.4	±4	±4				
LowC_2	1.8	3.6	17	16	2840	528	95WTW[2]	115TTW
	±0.5	±0.4	±5	±7	±210	±270		
BASE_3	3.9	4.3	24	26	(2900)	(625)	(115TTW)	(115TTW)
	±0.4	±0.5	±7	±8				
RBC_3	3.3	4.3	24	26	(2600)	(300)	(95WTW)	(115TTW)
	±0.8	±0.5	±7	±8				

Scen_Exp	ICE fcons	PHEV fcons	PHEV elcons	BEV elcons	fuel C.int	ener. C.int	ICE C.lim	PHEV C.lim
LowC_3	2.9	3.9	19	26	2800	318	95WTW[3]	none[5]
	±0.9	±0.7	±5	±8	±200	±79	95TTW[4]	115TTW[6]
BASE_4	3.8			14	(2900)	(625)		
	±0.2			±4				
RBC_4	3.8			14	(2600)	(300)		
	±0.2			±4				
LowC_4	3.5			13	2600	319		
	±0.04			±2	±0	±77		
BASE_5	4.6	6	18	10	(2900)	(625)	(105TTW)	
	±0.6	±0	±0	±0				
RBC_5	3.9	6	18	10	(2600)	(300)	(95TTW)	
	±0.3	±0	±0	±0				
LowC_5	3.6	6	18	10	2600	301	95TTW	
	±0.1	±0	±0	±0	±0	±15		

[1]All values in brackets are assumptions of the respective scenarios; [2]with 97% probability;
[3]with 75% probability; [4]with 25% probability, [5]with 57% probability; [6]with 43% probability

Abbreviations and Units:

Scen_Exp – scenario name and expert no.; fcons – fuel consumption (l/100km);
elcons – electric energy consumption (kWh/100km); fuel C.int – fuel carbon intensity (gCO_2/l);
ener. C.int – electric energy carbon intensity (gCO_2/kWh); C.lim – EU car CO_2 emission limit (gCO_2/km)

share for PHEV under LowC with an the expected value of nearly 70%. Electric drive shares for PHEV will be discussed later (see Section 4.5.4.4).

For the remaining two experts who have included PHEV in their BBN and have specified sales shares, the expected values for PHEV fuel consumption are insensitive to the different scenarios. They are 3.6 l/100km for expert 2 and 6 l/100km for expert 3, regardless of what scenario is chosen.

Similar to what has been done for combustion engine emissions, it can be analyzed how emissions from electric propulsion develop under the LowC scenario. To this aim, electric energy carbon contents as well as PHEV (in EV mode) and BEV electric energy consumption have to be discussed.

The minimum possible electric energy carbon content implemented within the BBN is 300 gCO_2/kWh, the level instantiated under the RBC scenario. BASE energy carbon content is 625 gCO_2/kWh. From the second column in the second block in Table 4.12, energy carbon contents can be seen. In the BBN of three experts (experts 3 throughout 5), expected values for LowC carbon intensity of electric energy are close to their minimum, at 318, 319 and 301 gCO_2/kWh, respectively. Expert 1's BBN yields an intermediate value of 385 gCO_2/kWh, and expert 2's BBN sets it closer to the BASE value at 528 gCO_2/kWh. In contrast to fuel carbon intensities, none of the BBN goes down to the minimum possible value.

Electric energy consumption of PHEV in electric mode and of BEV is displayed in the third and fourth column of the first block in Table 4.12. For PHEV, two experts (experts 2 and 5) do not specify any significant change in their expectations on energy consumption, no matter what scenario. In the BBN of one expert (expert 3), the expected value of PHEV energy consumption decreases by roughly 20% under LowC as compared to BASE or RBC. Still, he expects PHEV to consume slightly more electric energy (19 kWh/100km) than the other two experts who include PHEV into their BBN (17 and 18 kWh/100km).

As regards BEV, energy consumption is assessed to be insensitive to the different scenarios in two cases (BBN of experts 3 and 5). In one BBN, that of expert 4, the expected value decreases from 14 to 13 kWh/100km from BASE and RBC to LowC. For the remaining two BBN, there is an increase in BEV energy consumption from BASE and RBC to LowC; from 12 to 15 kWh/km for expert 1 and from 14 to 16 kWh/km for expert 2.

This striking result can be explained as follows: In the BBN of expert 1, BEV battery weight is fixed to a hundred kilograms and BEV range to 100 km. Thus, BEV energy consumption directly results from battery energy density, as the vehicle consumes the energy stored in a 100 kg battery within 100 km. Under BASE and RBC, battery energy density is instantiated at the lower state. Under LowC, it is not instantiated and this leads to a higher density, resulting in a higher BEV energy consumption. In the case of expert 2, the BEV battery has roughly 50% more capacity to store energy under LowC than under BASE, predominantly due to lower battery cost. The higher battery energy density under LowC compared to BASE only partly offsets the weight effect, such that the probability distribution on battery weight under LowC puts more probability on heavier batteries than that under BASE. The extra weight of the vehicle causes higher energy consumption.

Summing up, most BBN propose that BEV and PHEV in electric mode have an equal or higher energy consumption under LowC than under RBC. Moreover, energy carbon intensity is at least as high under LowC than under RBC. Thus, there is little room for electric propulsion to improve on the emission level of RBC. There is only one exception: Due to lower energy consumption, PHEV emissions under the LowC scenario are reduced to 60 gCO_2/km compared to 72 gCO_2/km under RBC in the BBN of expert 3. In all other cases, electric propulsion reaches its minimum emissions under RBC.

Up to now, it has been discussed how fuel and energy consumption develop under LowC. In the BBN, fuel consumption depends on the state of EU CO_2 emission regulation. Using the bottom-up approach of fixing fleet emissions, it is interesting to see which EU CO_2 emission limits for ICE and PHEV the respective BBN have triggered in the case of lowest possible fleet emissions. Results can be seen from the third block in Table 4.12. While two experts have eliminated the fuel consumption regulation nodes, the remaining BBN assign great likelihood to tight ICE CO_2 emission limits being in place if emissions are low. In the BBN of experts 2 and 5, the strictest possible policy for ICE, i.e., an emission limit of 95 gCO_2/km WTW, is assumed to be in place with 100% probability. In the BBN of expert 3, the same regulation is issued with 75% of probability, the remaining 25% going to the second strictest regulation.

For PHEV, expert 2's BBN finds that an emission limit of 115 gCO_2/km TTW is in place (the only other state for PHEV being that there is no regulation). Expert 3's BBN assigns 43% of probability to the regulation being issued, i.e., it is more probable not to have been implemented.

In summary, for the ICE emission limit, requirements under the LowC scenario correspond roughly to the regulation taken under the RBC scenario. Consequently, within the three BBN of experts who consider that regulation has an effect, it is an important prerequisite for driving down emissions. In contrast, a regulation for PHEV emissions is not important as results from most experts' BBN.

Summary of Scenario Effects on 2030 German New Car Fleet CO_2 Emissions

In this section, options for reducing CO_2 emissions from the 2030 German new car fleet below BASE levels have been evaluated. As a conclusion from the first paragraph, it can be said that experts' BBN produce divergent results in regard to the effects of single measures such as introducing more biofuels into the fuel mix, increasing the share of renewable electricity, or tightening the planned EU CO_2 emission regulation. However, a combination of these three measures has turned out as a robust approach for being reasonably certain to draw 2030 new car fleet emissions down to 100 gCO_2/km WTW, at most. While the biofuel and EU regulation components affect ICE emissions, the renewables component is needed to reduce PHEV and BEV emissions, as these vehicles are no low-emitting alternative when running on the current electricity mix. Under this set of measures, the range of expected fleet emissions of the five experts' BBN is 80 to 96 gCO_2/km, and the one sd area covers 60 to 100 gCO_2/km. Thus, under RBC, the 2030 new car fleet would emit roughly half as much as the 2008 new car fleet. For comparison, 2030 fleet emission expectations under BASE have settled to 96 to 128 gCO_2/km, with the one sd error bars extending roughly from 80 to 140 gCO_2/km.

Moreover, the LowC scenario has demonstrated that emissions can reach a lower level than induced by any of the policies or measures or combinations thereof analyzed within the other BBN scenarios. In the two BBN of experts 1 and 2, where the lowest emissions are reached (30 to 40 and 50 to 60 gCO_2/100km WTW, respectively), this can be done mainly by reducing ICE fuel consumption to extremely low levels of 1.2 and 1.8 l/100km. Fuel and energy carbon contents are somewhat lower than today, but do not need to go to the minimum possible values in the BBN. In two BBN where fuel consumption can not go below 3.5 l/100km (those of experts 4 and 5), fuel and energy carbon contents are driven down to their minimum and close to their minimum, respectively. Moreover, the fleet contains slightly more PHEV or BEV than under BASE or RBC, and in the case of expert 4, BEV consume a little less energy. However, there are no big changes compared to BASE. In the BBN of expert 3, PHEV play a dominant role. Emission reductions to an average of 70 to 80 gCO_2/km can be brought about by a mixture of components, predominantly by reduced PHEV energy consumption in electric mode, a low carbon intensity of energy, and some reduction in fuel consumption of both PHEV in combustion engine mode and ICE.

However, it has to be emphasized that none of the options for policy or technological development implemented in the top-down BBN scenarios suffice for driving fleet emissions down to their technically feasible minimum. Minimum emissions are reached only under the bottom-up LowC scenario, where they are enforced by setting fleet emissions to their lowest possible state. Thus, in the absence of any further policy measures or technological breakthroughs, and without a major change in paradigms among OEM, it is very unlikely that this path will be taken. This is expressed by the low probabilities the set of BBN assigns to extremely low emissions under all settings representing the current state of affairs. Thus, to move down towards lowest possible emissions, a shift in paradigms would have to be initiated, be it by OEM themselves, through a radical change in consumer demand patterns, or by a redesign of policy (other than the gradual strengthening of regulations as included into the BBN).

4.5.4.2 Vehicle Costs

When discussing what emission levels can be reached in which way, it is important to take into account the costs of the respective measures. A realistic and responsible approach to the issue can not blank out the possibly far-reaching economic consequences. Strong car CO_2 emission reduction can have effects, positive or negative, on production costs, OEM competitiveness and employment, to name just a few points. In regard to emission reducing technology, substantial R&D expenses are at stake, and the costs of newly introduced technologies may be high. These concerns are especially vital in a country like Germany, where the car industry is an important and powerful economic sector.

However, the BBN presented here is unable to cover the whole subject area and to come up with a macroeconomic cost assessment. Some of the measures proposed for bringing down car CO_2 emissions, such as the introduction of greater shares of renewable energies or biofuels, basically concern the energy sector and can not be discussed here in-depth. For the sake of manageability of the BBN, some coarse assumptions have been made in regard to the possible size of such shares, without explicitly modeling the effect on fuel and energy price development.

Incremental Vehicle Costs

In contrast, experts' assessments of the costs of new car technologies have been included into the BBN. Experts were asked to specify the average incremental costs of 2030 vehicles of all types as compared to average ICE costs in 2008. To get their assessments of vehicle-side costs of emission reductions, ICE and PHEV incremental costs were modeled conditional on their fuel consumption. For restricting the attention to vehicle technology, battery costs for both PHEV and BEV were excluded from this assessment and brought in elsewhere in the BBN. It is assumed that the experts' cost assessments cover the production costs for the vehicles as well as a share of development costs for the respective technologies, such that selling the vehicles at a price covering these costs, OEM would incur no losses.

Table 4.13 shows 2030 fuel and electric energy consumption of the different vehicle types alongside with their incremental costs compared to the average costs of a 2008 ICE vehicle. Values under BASE, Cpol, and LowC are included into the table as far as available in the different experts' BBN. While BASE assessments are available for all seven experts, Cpol is omitted for the two experts who have eliminated this option from their BBN (experts 1 and 4), and LowC is missing for the two experts who did not give 2030 sales shares (experts 6 and 7).

First, the BASE scenario has been chosen as a point of reference. From this scenario, it can be seen, e.g., by how much experts assume ICE costs to increase autonomously by 2030, i.e., in the absence of strong changes in parameters or extra measures. Second, the Cpol scenario has been added in order to examine the impact of a stricter EU CO_2 emission limit on vehicle costs. Compared to the RBC scenario, Cpol imposes the same emission limit, but does not enforce an increase in renewable electricity or biofuel shares.

Table 4.13: 2030 Vehicle Fuel and Energy Consumption and Related Incremental Costs

(Table continued on next page)

Scen_Exp	ICE fcons	PHEV fcons	PHEV elcons	BEV elcons	ICE costs	PHEV costs	BEV costs
BASE_1	3.5			12	1360		2000
	±0.7			±0	±1200		±580
LowC_1	1.2			15	3020		2010
	±0.1			±4	±1200		±580
BASE_2	4.5	3.6	17	14	500	−306	−547
	±0.3	±0.4	±4	±4	±290	±490	±650
Cpol_2	3.2	3.6	17	14	1420	−306	−547
	±0.9	±0.4	±4	±4	±1400	±490	±650
LowC_2	1.8	3.6	17	16	2590	−303	−571
	±0.5	±0.4	±5	±7	±1200	±490	±590

Scen_Exp	ICE fcons	PHEV fcons	PHEV elcons	BEV elcons	ICE costs	PHEV costs	BEV costs
BASE_3	3.9	4.3	24	26	3490	−299	−2300
	±0.4	±0.5	±7	±8	±1100	±490	±1400
Cpol_3	3.3	4.3	24	26	3860	−299	−2300
	±0.8	±0.5	±7	±8	±770	±490	±1400
LowC_3	2.9	3.9	19	26	3910	−186	−2310
	±0.9	±0.7	±5	±8	±740	±540	±1400
BASE_4	3.8			14	2000		−1850
	±0.2			±4	±580		±710
LowC_4	3.5			13	2010		−1930
	±0.04			±2	±590		±690
BASE_5	4.6	6	18	10	2100	2000	−499
	±0.6	±0	±0	±0	±730	±580	±290
Cpol_5	3.9	6	18	10	728	2000	−499
	±0.3	±0	±0	±0	±640	±580	±290
LowC_5	3.6	6	18	10	502	2020	−504
	±0.1	±0	±0	±0	±290	±600	±300
BASE_6	4.5	5.6	25	26	953	166	501
	±0.3	±1.2	±7	±7	±800	±930	±290
Cpol_6	2.7	5.6	25	26	3580	167	501
	±0.9	±1.2	±7	±7	±1000	±930	±290
BASE_7	4.1	4.3	30	22	2830	2370	-0.7
	±0.9	±0.4	±6	±5	±1900	±970	±290
Cpol_7	2.3	4.3	30	22	6500	2370	-0.7
	±0	±0.4	±6	±5	±870	±970	±290

All figures are expected values ± one standard deviation.

Abbreviations and Units:

Scen_Exp – scenario name and expert no.

fcons – fuel consumption (l/100km)

elcons – electric energy consumption (kWh/100km)

costs – incremental costs for the respective vehicle in 2030 compared to a 2008 ICE (€$_{2008}$)

(Table continued from previous page)

Cpol has been chosen here because changes in the fuel and electricity mix do not have an impact on vehicle costs in the BBN. Costs as displayed for the Cpol scenario are valid for the RBC scenario, as well, and Cpol fuel and energy consumption levels coincide with RBC levels. Third, the LowC scenario is included into the discussion of costs because it is of interest to find out what is the order of magnitude of costs linked to the strongest possible reduction in fleet CO_2 emissions.

Although fuel and energy consumption levels have been discussed in detail in the previous Section 4.5.4.1 and have been shown in Table 4.12, they have also been included into Table 4.13 for most of the experts and scenarios discussed here. On the one hand, this allows adding information for experts 6 and 7 which has not been given so far. On the other hand, displaying incremental costs alongside with fuel consumption figures permits to directly read off what consumption levels are linked to which cost changes.

From Table 4.13 it can be seen that under the BASE scenario, expected values of ICE cost increments until 2030 are in the range of roughly 500 to 3500 €$_{2008}$, with a majority of four experts' BBN yielding increases of 2000 €$_{2008}$ and more. 2030 BASE ICE fuel consumption takes expected values from 3.5 to 4.6 l/100km. When moving from the BASE to the Cpol scenario, expected ICE fuel consumption drops by 0.6 to 1.8 l/100km in the single BBN, resulting in expected consumption levels of 2.3 to 3.9 l/100km over the five BBN where Cpol can be run. The Cpol incremental cost range for ICE is about 700 to 6500 €$_{2008}$ per car. In all but one BBN, Cpol causes cost increases compared to BASE. In the two BBN which start from the lowest BASE costs (the BBN of experts 2 and 6), cost increments nearly triple and more than triple, but also for others, there are major increases. In contrast, in one BBN (that of expert 5), ICE incremental costs drop to a third of their BASE value under Cpol.

LowC can not be run within the BBN of experts 6 and 7, which yielded relatively high ICE incremental costs under Cpol. The range of LowC ICE incremental costs for the remaining five BBN is 500 to 3900 €$_{2008}$, thus roughly as under BASE. For the single BBN, compared to BASE, LowC incremental costs are more than doubled for one BBN, quintupled for another one, barely and moderately increased for two more, and reduced to a quarter for a fifth one. The LowC fuel consumption range is 1.2 to 3.6 l/100km. Thus, while ICE fuel consumption decreases from BASE to Cpol to LowC, there is a trend of increasing costs that holds for most, but not for all BBN.

Expected values of PHEV incremental costs (excluding the battery) under BASE range from −306 to 2370 €$_{2008}$. Two experts' BBN suggest that 2030s PHEV will be cheaper than today's ICE, one proposes that they will cost less than 200 €$_{2008}$ more, and the remaining two place assessments in the upper area of the range. For most BBN, 2030 PHEV costs barely react to the changes modeled in the scenarios. From BASE to Cpol, no BBN produces a significant change; in fact, only one of the BBN yields a change at all, which is plus 1 €$_{2008}$. From BASE to LowC, two BBN show minimal incremental cost increases in the range of 1%, and a third one suggests that they will increase from −299 to −186 €$_{2008}$. For two further BBN, no LowC assessments are available. The LowC PHEV incremental cost range is −303 to 2020 €$_{2008}$. The expected values for PHEV fuel consumption are 3.6 to 6 l/100km under BASE, and hardly differ for other scenarios. Cpol fuel consumption does not diverge from BASE values at all, and under LowC, there is just one BBN within which PHEV fuel consumption will be 3.9 instead of 4.3 l/100km, which does not change the overall range of assessments. The same holds for PHEV energy consumption, which does not react to the different scenarios except for one case, where it is lower under LowC than under BASE (19 instead of 24 kWh/100km in the BBN of expert 3). The BASE and Cpol range of PHEV energy consumption is 17 to 30 kWh/100km.

For BEV, the range of expected values for BASE incremental costs is −2300 to 2000 €$_{2008}$. Within this interval, two experts' BBN yield low expected values of around −2000 €$_{2008}$, two propose roughly −500 €$_{2008}$, one assessment is close to 0 €$_{2008}$, and the remaining two result in positive cost increments of 500 and 2000 €$_{2008}$. As for PHEV, cost variations over scenarios are minor. From BASE to Cpol, none of BBN suggests that costs will change at all. But as Cpol can not be implemented within two BBN, the related range of incremental costs narrows down to −2300 to 500 €$_{2008}$. There are no changes in BEV electric energy consumption from BASE to Cpol.

Of the five experts' BBN for which the LowC scenario can be run, three suggest 2030 BEV to be cheaper under that scenario than under BASE, assuming decreases in the expected value of cost differences of less than 100 €$_{2008}$. The remaining two propose cost increases, one of them a minor one of 10 €$_{2008}$, the other one a major increase of around 1000 €$_{2008}$. From BASE to LowC, there are slight increases in BEV energy consumption in two cases and a slight decrease in a further case.

Under all scenarios not included in Table 4.13, incremental costs for 2030 vehicles are scarcely different from BASE costs[25], with one exception. Within the BBN of expert 7, ICE and PHEV incremental costs react to the higher fuel price scenario (FP), as well. Under that scenario, fuel consumption expected values go down from 4.1 to 2.3 l/100km for ICE, and from 4.3 to 3.5 l/100km for PHEV. This is linked to an increase in the cost increment to 6490 (± 870) €$_{2008}$

[25]As mentioned, RBC incremental costs are equivalent to Cpol incremental costs for all BBN where Cpol is available.

for ICE, which is more than twice the increment under BASE, and 4000 ($\pm$ 580) €$_{2008}$ for PHEV, which is an increase by two thirds of the BASE price increment. This strong reaction is due to the optimization routine implemented in the BBN of expert 7, which adjusts fuel consumption such that annual vehicle costs are minimized (for the details, see Section 4.4.5). For all other experts' BBN, price increments under the FP scenario are minor.

Summing up what has been said on incremental costs, it has been found that:

- ICE are very likely to cost more in 2030 than today. Expectations derived from the different experts' BBN in regard to cost differences are between roughly 500 and 3500 €$_{2008}$, or between 700 and 6500 €$_{2008}$, depending on how much regulatory pressure is exerted to reduce their fuel consumption.
- Producing a 2030 PHEV, excluding the battery, may cost slightly less (down to -300 €$_{2008}$) or up to 2400 €$_{2008}$ more than the production of a current ICE, regardless of the scenario.
- 2030 BEV cost differences to current ICE, excluding battery costs, spread from roughly -2300 to 2000 €$_{2008}$, without different scenarios causing much of a change in expectations.
- Comparing cost increments, it turns out that 2030 ICE are likely to be more expensive than any of the other vehicle types. A stricter limit on ICE fuel consumption tends to make them more expensive and thus amplifies this tendency.

In fact, taking another look at Table 4.13 and selecting the vehicle where expected cost increments are lowest from each line, it turns out that this is the BEV for most experts and scenarios. Within four experts' BBN, BEV are the least expensive 2030 vehicles no matter what scenario, and within one, PHEV are always the cheapest option. There are only two cases where 2030 ICE win this comparison (i.e., BASE_1 and LowC_5).

Consequently, it can be said that experts do not expect the technology needed to produce PHEV or BEV to be very costly, compared to the cost development of today's standard type of vehicles. On the contrary, BBN results suggest that 2030 ICE vehicles will be more expensive than PHEV or BEV, which may result from more expensive technology, materials used, or labor costs caused by their production. Whatever the cause for higher ICE costs, the technology needed for PHEV and BEV on the vehicle side is unlikely to cause any cost problems. Thus, while a general increase in costs over all car types may cause a reduction in car demand unless real wages grow at a similar pace, it can not be said that PHEV or BEV suffer a competitive disadvantage compared to ICE due to costs on the vehicle side.

Battery Costs
However, the cost assessments for PHEV and BEV discussed so far do not include the costs of the battery. As large batteries are not part of the current core business of car manufacturers and as the development of battery prices until 2030 is uncertain, experts have not been asked to give assessments of battery costs in 2030, but only to provide specifications of the amount of energy PHEV and BEV batteries will need to store. Battery prices are dealt with via scenarios within the BBN.

Table 4.14 provides assessments of battery costs for PHEV and BEV in 2030 which result from combining experts' statements on PHEV and BEV overall battery energy with the battery price assumptions made within the different scenarios. These battery costs have to be added to the incremental costs just discussed (and displayed in Table 4.13) in order to get a complete picture of the cost differences for the different car types. These cost differences are likely to translate into sales prices, as OEM will not accept to incur losses from selling any of their vehicles over the longer term.

As can be seen from Table 4.14, under the BASE scenario, expected values the different BBN assign to battery costs are in the range of 5360 to 21000 €$_{2008}$ for PHEV, and 6400 to 45000 €$_{2008}$ for BEV. Under the BAT scenario, which assumes favorable battery development, ranges are 2150 to 7000 €$_{2008}$ for PHEV, and 3000 to 15000 €$_{2008}$ for BEV. As battery prices under BAT are one third of those under BASE, it is little surprising that BAT batteries are much cheaper. Expert 5 has denied that battery prices could reach a level as low as assumed under BAT until 2030. Nevertheless, results from running his BBN under the BAT scenario have been included in Table 4.14 as well as in the later description of BAT outcomes in order to show the effects of low battery costs on his assessment. It has to be kept in mind that the expert himself would doubt that such results are within reach.

Apart from BASE and BAT, the LowC scenario has been included into Table 4.14. Evidently, LowC battery cost ranges are somewhere between those for BASE and BAT. For all scenarios not included in the table, battery costs are at BASE level. Taking a look at the limits of battery costs under BASE and BAT, it is obvious that very large battery price ranges are covered. To what area within the given ranges battery costs will actually settle depends on how much battery the vehicles will carry. This, in turn, is predetermined by decisions regarding their weight and shape, and for BEV, regarding the distance

Table 4.14: PHEV and BEV 2030 Battery Costs (€$_{2008}$)

	Exp. 1	Exp. 2		Exp. 3		Exp. 4	Exp. 5		Exp. 6		Exp. 7	
	BEV	PHEV	BEV	PHEV	BEV	BEV	PHEV	BEV	PHEV	BEV	PHEV	BEV
BASE	7200	5360	12600	7790	18300	9000	21000	9000	5840	6400	9010	45000
	±0	±1600	±5100	±2400	±5800	±1700	±0	±0	±2300	±920	±1700	±8700
BAT	4000	2150	9210	3180	9600	3300	7000	3000	7000	9000	3000	15000
	±0	±670	±2000	±1400	±1700	±1100	±0	±0	±1700	±580	±580	±2900
LowC	5850	4170	11400	5670	13600	5530	13900	5950				
	±3400	±2200	±4800	±3500	±6600	±3000	±7000	±3000				

The table displays experts' expected values ± one standard deviation for 2030 PHEV and BEV battery costs under different scenarios.

they have to be able to cover with one charge of the battery. The differences in battery capacities and thus costs among different experts' BBN are due, to a large extent, to experts' anticipation of what consumers will want their 2030 PHEV and BEV to be like.

As the large range of assessments shows, the configuration of 2030 PHEV and BEV may become even more important for their market chances than battery price development. At the upper limits of PHEV and BEV battery costs under BASE, it can be excluded that a meaningful share of car buyers will be ready to pay a markup of this size just to get a PHEV or BEV instead of an ICE. The same holds for the BEV upper battery price limit under BAT, and possibly even for PHEV under BAT, which still demand battery expenditures of up to 7000 €$_{2008}$. Thus, in case of battery capacities at the upper limit of assessments, either no important quantities of PHEV and BEV will be sold, or new business models will have to be found, e.g., battery renting or leasing models which reduce the effect of battery costs on vehicle sales prices.

In regard to the lower boundaries of the ranges, especially under BAT, market chances of PHEV and BEV look much better. Given that the vehicles without batteries may cost less than ICE, and given that expenses for electricity may be lower than fuel costs, PHEV and BEV equipped with smaller batteries may become attractive from an economic point of view under the BAT scenario. They may even sell at BASE battery prices. According to a survey among German car customers in 2010, a third of them was thinking about buying a BEV, half of which said that they were ready to pay a price markup of up to 4000 Euros (Berger 2010).

Summing up, the ability of PHEV and BEV to compete with ICE on the market in regard to sales prices depends on, first, the configuration of the vehicle and the resulting battery capacity needed, and second, battery price development. Of course, apart from vehicle costs and related sales prices, consumer preferences in regard to non-monetary aspects are decisive, as well. Depending on the configuration of 2030 vehicles, e.g., ICE and BEV may not be perfect substitutes. If a consumer wants a big, powerful car with a large range, she will not buy a city BEV even if its price is just a fraction of the price of a luxury class ICE, because she will not be satisfied with its range, size or comfort. Another consumer may be ready to pay a markup on the price of a comparable ICE if a BEV is exactly what she wants for daily commuting. There are many more arguments influencing consumer choices, which surpass the scope of the present BBN analysis. One important group of arguments strongly linked to the choice of a vehicle today are lifestyle and image aspects, which are beyond what could be modeled in the present approach.

Table 4.15: PHEV and BEV 2030 Annual Cost Differences compared to ICE (€$_{2008}$)

	Exp. 1	Exp. 2		Exp. 3		Exp. 4	Exp. 5		Exp. 6		Exp. 7	
	BEV	PHEV	BEV	PHEV	BEV	BEV	PHEV	BEV	PHEV	BEV	PHEV	BEV
BASE	494	153	750	386	1330	178	1920	28	393	467	987	4510
	±150	±210	±650	±320	±770	±250	±190	±180	±290	±260	±310	±1100
BAT	364	−202	424	−162	346	−464	344	−649	530	761	310	1130
	±150	±140	±310	±230	±350	±200	±190	±180	±280	±250	±190	±460
Cpol		397	934	472	1420		2240	340	482	556	959	4490
		±240	±650	±360	±790		±150	±140	±320	±290	±320	±1100
EVInc1	−70	−411	186	−178	769	−386	1360	−536	−171	−97	423	3959
	±150	±210	±640	±320	±770	±250	±190	±180	±290	±260	±310	±1100
EVInc2	364	46	592	237	1040	26	1730	-82	188	182	801	4280
	±150	±190	±620	±290	±730	±240	±190	±180	±250	±210	±270	±1100
FP	262	−49	441	237	1060	−72	1630	−283	161	165	1020	4360
	±180	±210	±650	±320	±760	±250	±220	±210	±290	±270	±310	±1100
LowC	375	70	717	−164	514	−596	1180	−226				
	±520	±400	±650	±550	±860	±400	±840	±430				

The table displays experts' expected values ± one standard deviation for PHEV and BEV annual cost differences to ICE in 2030, i.e., additional costs a consumer has to bear for owning and driving such a vehicle compared to an average ICE available in 2030.

Annual User Cost Differences

As for PHEV and BEV, batteries add a substantial share of total vehicle costs, this component has to be included into the assessment of what cars will sell. Battery costs have to be considered as a part of the sales price, assuming that battery costs are passed on to car buyers. Another aspect is that over a vehicle's lifetime, higher sales prices for PHEV and BEV may be (at least partly) compensated through lower operating costs.

In the present BBN, sales shares have been modeled to depend on the annual costs of a vehicle.[26] Apart from the costs of the vehicle and the battery, this includes maintenance costs and annual variable costs resulting from vehicle use, i.e., fuel or electric energy costs. In oder to reduce network complexity and simplify elicitation, instead of the absolute costs for each car type, 2030 PHEV and BEV annual cost differences compared to ICE have been modeled. ICE have been used as the numeraire in establishing fleet composition. This approach also has the advantage that vehicle maintenance costs do not need to be included into the annual cost difference, assuming that they are roughly equivalent for all vehicle types. The equation for calculating annual cost differences for PHEV and BEV to ICE has been documented in Section 4.3.

On the one hand, this modeling approach may be disputed because it is unclear in how far consumers base their vehicle choice on the annual costs they expect it to cause. When they make their purchase decision, they know the price of a vehicle, but may only have an imprecise idea of the fuel or electric energy consumption of that vehicle, given their personal driving style and profile, or of its maintenance costs. Even if consumers have a clear picture of vehicle consumption, the development of fuel and energy prices over the vehicle's lifetime is uncertain. On the other hand, it can be assumed that variable costs play some role in such decisions, and I found that including them in a possibly unrealistic way was better than not taking them into account at all. It turned out that none of the experts objected to assessing sales shares based on annual cost differences or found it especially challenging to provide conditional probabilities at this point.

Annual cost differences for PHEV and BEV compared to ICE are presented in Table 4.15. As before, the table gives expected values for each expert's BBN $\pm$ one standard deviation over a range of scenarios. It can be deduced that for most experts and scenarios, cost differences are positive, i.e., owning and driving PHEV or BEV is more expensive than using ICE. However, under certain conditions, expected annual costs of PHEV or BEV can be lower than those of ICE. This is the case in roughly 20% of the expert-scenario combinations.

[26]In addition, BEV sales shares have been modeled conditional on their range.

Scenarios where at least some experts expect PHEV or BEV to cost less include EVInc1 (a 5000 $€_{2008}$ purchase subsidy), BAT (favorable battery development), FP (higher fuel price), LowC (extreme CO_2 emission reductions), and EVInc2 (price for mobility-related electric energy fixed at a low level).

As Table 4.15 is too large for offering an easy overview, expected values from that table are displayed in Figure 4.41. It can be seen that under the BASE scenario, all experts' BBN result in PHEV and BEV more costly than ICE in 2030, on an annual basis.

For PHEV, under BASE, three out of five experts' BBN yield cost add-ons of less than 500 $€_{2008}$ compared to ICE, while maximum additional costs are nearly 2000 $€_{2008}$ p.a. PHEV relative costs are lowest under the BAT and EVInc1 scenarios. The range of expected values is most concentrated under the BAT scenario, where it is roughly -200 to 500 $€_{2008}$ for the five BBN. Within this range, outcomes from two BBN are placed in the area of the lower limit, and three close to the upper limit of the range. A second scenario reducing PHEV annual cost increments is EVInc1, where three BBN result in PHEV causing lower annual costs than ICE (-411 to -171 $€_{2008}$ p.a.), but two propose relatively high annual cost markups (423 and 1360 $€_{2008}$). For most experts' BBN, annual PHEV cost differences under EVInc2 and FP are also lower than under BASE, but higher than under BAT and EVInc1. For the three BBN where it is available, the LowC scenario also fosters relatively low annual PHEV cost increments compared to ICE. The stratification of experts' BBN in regard to their assessments of PHEV expected annual cost differences to ICE is relatively stable over scenarios. The BBN of experts 2, 3 and 6 nearly always give the lowest estimates. All negative cost assessments can be assigned to these three networks, and they hardly pass the 500 $€_{2008}$ mark. The BBN of experts 5 and 7 yield higher PHEV cost add-ons, which are nearly always above 500 $€_{2008}$ and range up to more than 2000 $€_{2008}$ p.a for the BBN of expert 5.

For BEV, under BASE, expected annual add-ons are below 200 $€_{2008}$ within two BBN, roughly 500 $€_{2008}$ within two more, and from 750 up to 4500 $€_{2008}$ within the remaining three. As for PHEV, the BAT scenario narrows down the range of assessments (to -649 to 1130 $€_{2008}$ p.a.)[27]. For EVInc1, four experts' BBN (experts 1, 4, 5 and 6) propose that BEV will be cheaper than ICE. For BAT, FP and LowC, two BBN yield this result (those of experts 4 and 5, while expert 5 has contested the idea that 2030 battery prices could reach BAT levels), and for EVInc2 only one BBN (that of expert 5). Except for the BAT scenario, the BBN of expert 7 always shows BEV to cost at least 4000 $€_{2008}$

[27]The range of assessments is even smaller under LowC (-596 to 717 $€_{2008}$), but due to the fact that no assessment is available from expert 7.

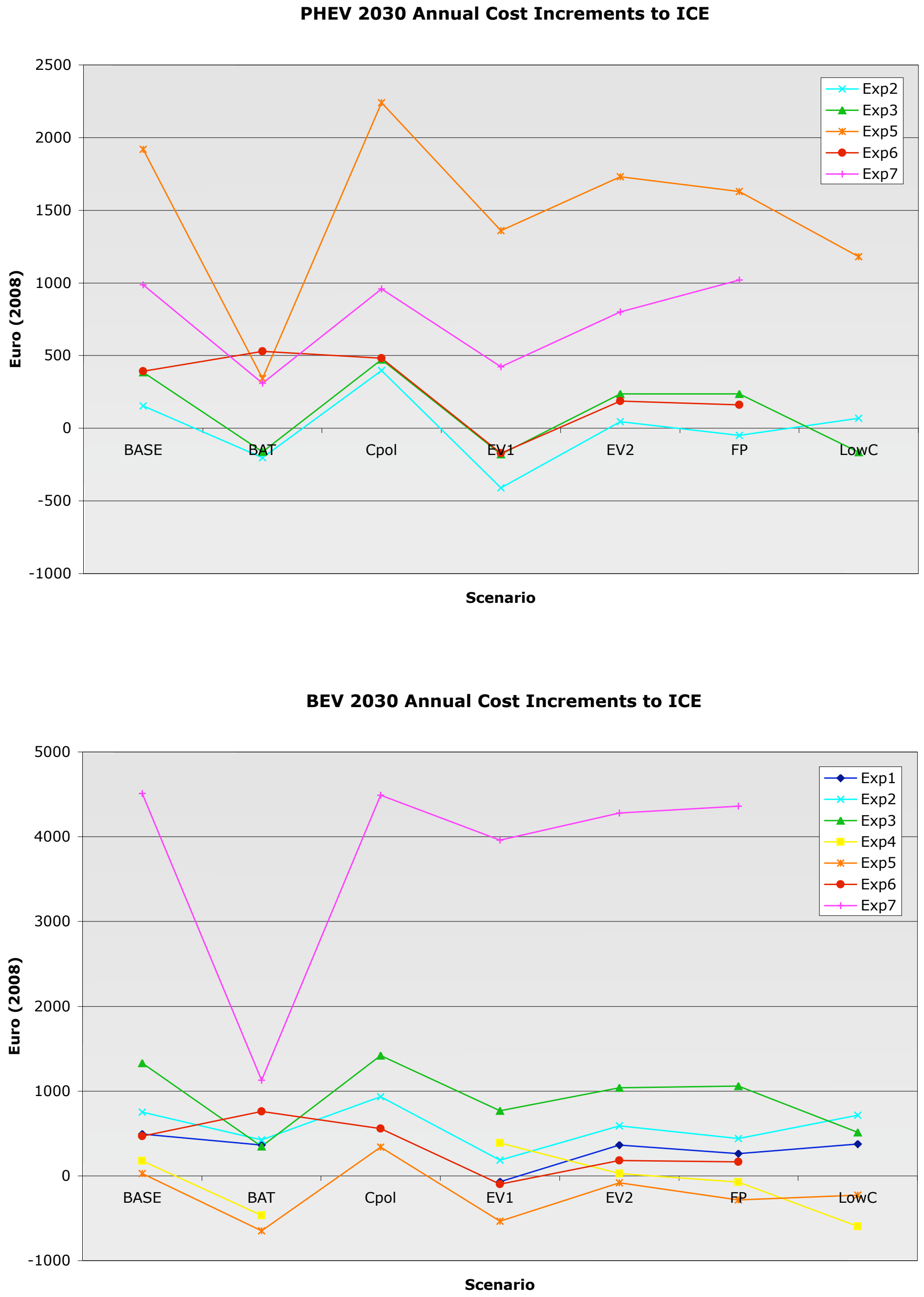


Figure 4.41: 2030 PHEV and BEV Annual Cost Differences under Different Scenarios (Expected Values)

more than ICE, annually. For most scenarios, the remaining BBN suggest that BEV cost from a few hundred €$_{2008}$ up to a thousand €$_{2008}$ more than ICE, each year. As for PHEV, BAT and EVInc1 are the scenarios where the lowest BEV annual cost increments are reached, and under EVInc2 and FP, they are higher, but lower than under BASE. The BBN of expert 5, which assigned the highest annual incremental costs to PHEV under almost each scenario, is the BBN which yields the smallest relative annual costs for BEV under nearly every scenario.

Summing up, in the absence of any measures or developments favorable for BEV and PHEV, they are likely to be more expensive in 2030 than ICE. Under the baseline scenario, for BEV, two BBN suggest expenses of 200 €$_{2008}$ on top of ICE, but a majority of BBN results in markups of at least 500 €$_{2008}$ or even much more. For PHEV, one BBN produces an add-on of 150 €$_{2008}$, but all others yield incremental costs of 400 €$_{2008}$ or much more, annually. Scenarios that can help reducing PHEV and BEV expenses, and even draw their annual costs below ICE levels in the view of some experts, are mainly the BAT and EVInc1 scenarios. The EVInc2 and FP scenarios have favorable effects, but cost increments are generally lower under BAT and EVInc1. The mechanism under FP is that ICE (and PHEV combustion engine mode) operating costs increase and thus make BEV, as well as PHEV with a large electric range, relatively more attractive.

4.5.4.3 Vehicle Types' Sales Shares

In the BBN, sales shares depend on annual vehicle cost differences of the vehicle types, and, for BEV, on their range. Under BASE, BBN results show that both 2030 PHEV and BEV will be more expensive than ICE. Thus, market chances of PHEV and BEV depend on the willingness of consumers to pay more for them than for an ICE vehicle. Complete probability distributions for 2030 new fleet composition have been presented and discussed in Section 4.5.3.3 (see Figure 4.33). It has been demonstrated that under BASE, most BBN suggest that ICE will still be the standard type of 2030 vehicles, while one expert's BBN attributes similar importance to PHEV.

In this section, only expected values will be discussed. Figure 4.42 shows the BBN results regarding 2030 sales shares of all vehicle types under different scenarios. For some scenarios, there are no changes in sales shares compared to BASE, which is the case whenever neither the cost relations of the vehicles nor BEV ranges differ from BASE values. This concerns the scenarios REN and BF, thus they are subsumed under the BASE scenario in Figure 4.42.

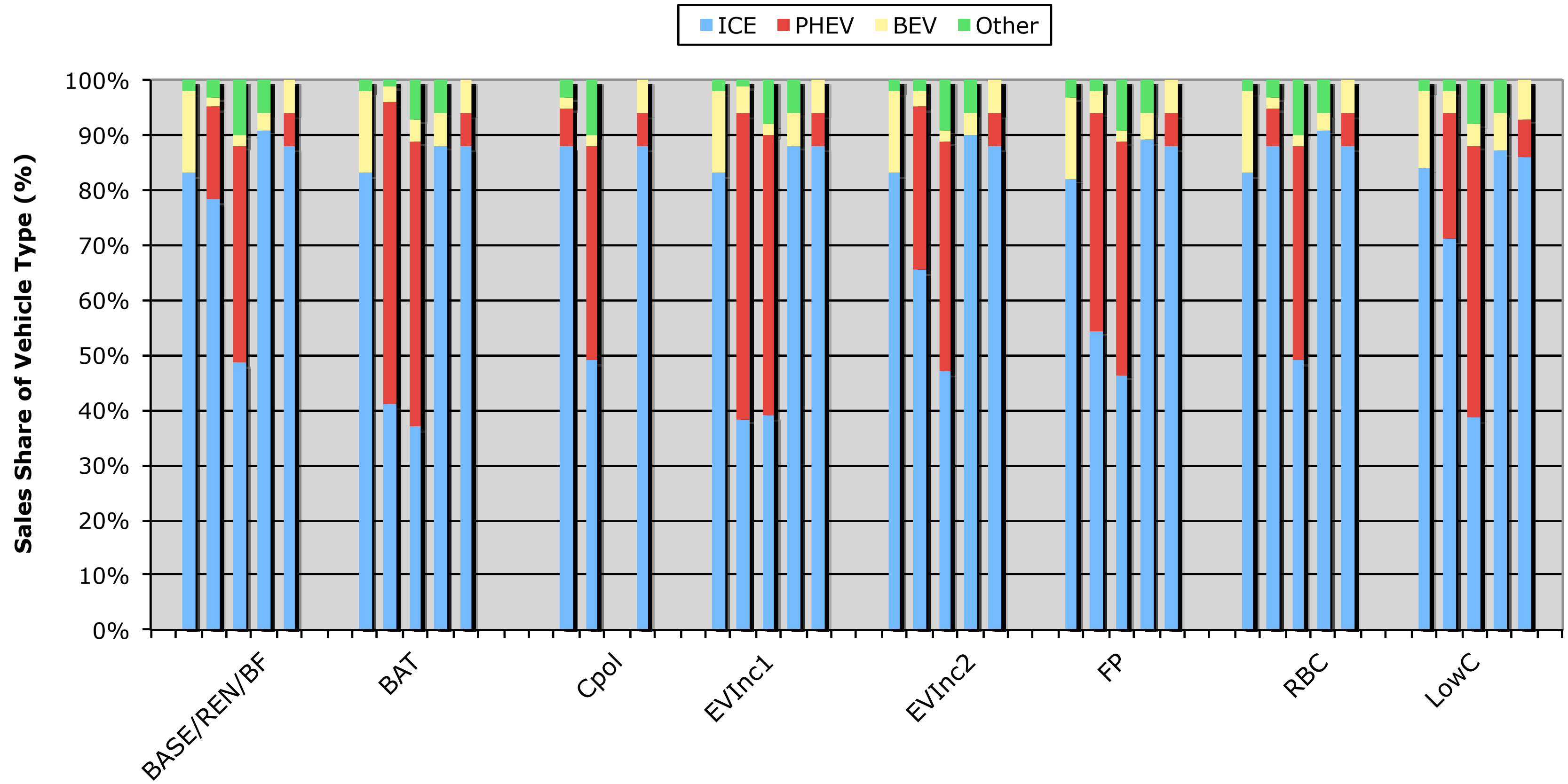


Figure 4.42: 2030 Vehicle Types' Sales Shares under different Scenarios (Expected Values)

Each bar gives one expert's expected values for ICE, PHEV, BEV and Others' sales shares in the 2030 new fleet. Blocks of bars relate to different scenarios. The five bars within the scenario blocks relate to experts 1 throughout 5, except for Cpol, where bars relate to experts 2, 3 and 5.

As can be seen from Figure 4.42, within the BBN of experts 1 and 5, sales shares do not respond to any of the scenarios. They stick to zero PHEV and 15% (± 5% sd) of BEV for expert 1, and 6 ± 1% of PHEV and BEV, each, for expert 5. This is due to the category schemes these experts have used for annual cost differences. Expert 5 has excluded PHEV annual cost increments of less than 2000 €$_{2008}$ compared to ICE, and both experts have assigned zero probability to BEV cost increments in the negative area. However, even under BASE, within their BBN, a probability of zero is calculated for annual cost increments reaching the higher one of the two annual cost categories each of these experts has considered. Consequently, there is just one incremental cost category within each of these BBN (because the others are attributed zero probability), and sales shares can not react to changes in relative costs. With the measures reducing PHEV and BEV costs implemented in some scenarios, annual cost increments move further down towards values that have not been considered by the experts. Actually, negative annual cost differences for PHEV or BEV are incompatible with the expectations of these two experts. However, in order not to lose the information on sales shares contained in their BBN, I have assumed that in case lower costs are realized, the same number of PHEV and BEV can be sold as in the case of higher costs.

For the remaining experts' BBN, 2030 sales shares vary over the different scenarios. PHEV market shares vary most strongly for expert 2. Under BASE, his BBN assigns an expected share of 17% to PHEV. Under BAT and EVInc1, PHEV are the dominant vehicle type, with expected market shares of 55%. In his BBN, PHEV also have elevated shares of 40% under FP, 30% under EVInc2, and 23% under LowC. Under Cpol and RBC, their share is smaller than under BASE, at an expected value of 7%. This corresponds to the PHEV expected annual cost differences to ICE discussed in the previous section. For expert 2, they are negative under BAT, EVInc1, and FP, and positive and higher than under BASE for Cpol and RBC. For the same expert, BEV 2030 sales shares range from 2% to 5%, with EVInc1 yielding the highest share, and BASE, Cpol and RBC the lowest ones.

In contrast to all other BBN, that of expert 3 produces a 40% PHEV share even under the BASE scenario. Under BAT, EVInc1 and LowC, this share increases to 50% and slightly more. For the remaining scenarios, it is around 40%. BEV shares are 4% under BAT and LowC, and 2% under all other scenarios including BASE.

Expert 4 has not considered PHEV as a vehicle type in his BBN. BEV shares range from 3 to 7%, with the LowC, BAT and EVInc1 scenarios yielding shares at the higher end, and BASE and RBC at the lower end of the interval.

Experts 6 and 7 have not given any sales share assessments. For them, it can be tried to deduce some hints on the market chances of PHEV and BEV from the annual cost differences presented in the previous section (see Figure 4.41). For expert 6, PHEV incremental costs are roughly in the range of −200 to 500 €$_{2008}$, and BEV incremental costs span from −100 to 800 €$_{2008}$ p.a. While at negative cost increments, which are reached under the EVInc1 scenario, it can be imagined that PHEV and BEV gain at least some acceptance, it is impossible to infer what the assessment of the expert would have been. He has made no statement regarding his expectations on consumers preferences or willingness to pay. For expert 7, a rough guess can be made. If 2030 PHEV have a chance to acquire some market share at all, then under the BAT scenario (where they cost an annual 310 €$_{2008}$ on top of ICE), and possibly under the EVInc1 scenario (an annual 420 €$_{2008}$ on top). However, it can be assumed that the expert would have assigned only minuscule shares, given that he pointed out he expected consumers not to be willing to pay add-ons. For all other scenarios, PHEV annual cost differences to ICE are more than 800 €$_{2008}$ p.a., which makes them very unattractive. For BEV, the cost difference is always more than 1000 €$_{2008}$ a year, and often more than 4000 €$_{2008}$, which deprives them from any meaningful market chances.

Summarizing the findings on sales shares, evidence on the impacts of the different scenarios can hardly be generalized. Of the five experts who have specified sales shares, two have made their BBN unresponsive to annual cost changes in the range of values produced by the BBN. With respect to PHEV, only two of the remaining experts (experts 2 and 3) think that they may have significant market shares in 2030. Their BBN show that BAT and EVInc1 are the best and nearly equivalent measures for promoting PHEV, yielding ales shares of slightly above 50% for both experts. For the same two BBN, an increase in the 2030 fuel price (FP) leads to PHEV sales shares of at least 40%. In regard to BEV sales, three experts (experts 2 throughout 4) have produced responsive BBN with quantified sales shares. In their BBN, the overall share of BEV in the 2030 German new vehicle fleet is assessed to be minor. No matter what scenario is applied, it does not surpass 7%. There is no consensus on what measures do best promote BEV shares. The BBN of expert 2 yields its maximum BEV share (of 5%) under EVInc1, that of expert 3 under LowC and BAT (4%), and that of expert 4 under LowC (7%). The two BBN with fixed BEV shares (those of experts 1 and 5) suggest relatively high shares of BEV at 15% and 6%.

The present BBN can contribute some insight into how German OEM evaluate the market chances of PHEV and BEV. In the previous section, the sce-

Table 4.16: 2030 Electric Vehicles' Market Shares under BASE, BAT, and EVInc1 (%)

Scen.	Exp.	PHEV	BEV	Sum EV
BASE	Expert 1	0	15	15
	Expert 2	17	2	19
	Expert 3	40	2	42
	Expert 4	0	3	3
	Expert 5	6	6	12
BAT	Expert 1	0	15	15
	Expert 2	55	3	58
	Expert 3	52	4	56
	Expert 4	0	6	6
	Expert 5	6	6	12
EVInc1	Expert 1	0	15	15
	Expert 2	55	5	60
	Expert 3	51	2	53
	Expert 4	0	6	6
	Expert 5	6	6	12

The table presents the expected values for 2030 market shares of PHEV, BEV, and the sum of both (EV) as resulting from the BBN specified by Experts 1 troughout 5 under the scenarios BASE, BAT and EVInc1. Experts 6 and 7 have not quantified 2030 sales shares.

narios BAT and EVInc1 have been identified as the main scenarios leading to reductions in PHEV or BEV relative annual costs, and EVInc2 and FP to a lower degree. Table 4.16 summarizes expected PHEV and BEV market shares for the BASE, BAT and EVInc1 scenarios, and sums them up to an overall 'EV' market share. It can be seen that for the responsive BBN of experts 2, 3 and 4, the lower EV costs under BAT and EVInc1 can be found to translate directly into higher EV market shares. Within two of the BBN, this effect is brought about mainly by strong increases in PHEV market shares, and a third one shows a moderate increase in BEV market shares.

Overall, the assessments of EV market chances vary strongly among experts and scenarios. Under BASE, four BBN show ICE to remain the dominant vehicle type with market shares of around 80 to 90%, while one shows an ICE share below 50% with 40% PHEV. Under BAT and EVInc1, three BBN still yield more than 80% ICE shares, but two result in 50 to 60% EV shares, predominantly PHEV. BEV market shares are a few percentage points for four BBN, but 15% within the fifth one, no matter what scenario. However, a majority of four BBN under BASE and three BBN under more EV-favorable scenarios sticks to an ICE-dominated 2030 German new vehicle fleet.

Finally, it has to be added that modeling vehicle choices contingent on their annual cost differences may be a valid approach to fleet composition under the assumption that a consumer has decided to buy a passenger vehicle and is now left with the choice of a car type. However, the preceding decision of whether or not to buy a car is not included into the analysis. The absolute size of the 2030 new vehicle fleet depends on the absolute cost level, which is beyond the scope of the present approach. Absolute car fleet size may be as important an argument for the emissions caused as average car fleet emissions.

4.5.4.4 The Impact of Policies and Technological Development

Apart from looking for ways of reducing CO_2 emissions of the 2030 German new vehicle fleet, the BBN allow to examine the effect of different policies, as well as of battery development. In this section, these aspects will be discussed. Regarding policies, the scenario implementing a strict EU car CO_2 emission limit (Cpol) will be discussed, as well as the effects of consumer incentives for buying PHEV or BEV (EVInc1 and EVInc2). A short look will be taken at the impact of a higher fuel price (FP), as the fuel price in Germany is strongly influenced by taxation which can be driven from the political side. However, the effects of higher fuel prices do not depend on whether the price increase is brought about by policy. They will be the same in case market prices rise. Finally, for analyzing the effect of favorable battery development, the BAT scenario will be discussed.

Some of the information given in this section has been included elsewhere, as the effects of different scenarios on emissions, costs and vehicle market shares have already been discussed above. Still, there is added value in summarizing the information regarding individual scenarios, as it allows to judge the overall outcomes of specific measures.

The Impact of Policies

The **Cpol** scenario presupposes that at the EU level, a car emission limit of 95 gCO_2/km well-to-wheel is imposed, replacing the less demanding limit of 115 gCO_2/km tank-to-wheel which is assumed to be in place under BASE. Cpol can only be implemented in five out of the seven BBN. As has been shown in Figure 4.36 (Section 4.5.4.1), the range of expected values for Cpol fleet emissions over all BBN is shifted downwards by less than 10 gCO_2/km compared to BASE fleet emissions. This is predominantly brought about by reductions in ICE emissions, while the range of expected Cpol emissions of PHEV and BEV does not differentiate from that under BASE (see Figure 4.37).

Under Cpol, annual cost differences for both PHEV and BEV compared to ICE are a little higher for most experts' BBN than under BASE. Cpol market shares, which can be identified for three BBN only, show an increase of ICE by 10 percentage points to 88% at the expense of PHEV within one BBN, and no changes for the other two (Figure 4.42).

As a conclusion, a tightened EU car CO_2 emission limit of the form modelled in the BBN alone neither reduces emissions in a meaningful way in the view of most experts, nor brings about major changes in relative car user costs or 2030 new fleet composition. However, as discussed in Section 4.5.4.1, a tightened EU car CO_2 emission limit is necessary in order be reasonably sure to drive 2030 German new car emissions to a level of 100 gCO_2/km and less under a combined approach of measures (RBC) in all BBN. In the three BBN where the effect of Cpol could be modeled, it was essential to achieve this result. One of the experts who did not differentiate EU regulation scenarios (expert 4) already departed from the assumption that a 95 gCO_2/km TTW regulation (with 105 g on the vehicle side) would be implemented. Only one expert (expert 1) did not require such a regulation for achieving relatively low emission levels, but argued that global competition would drive down vehicle fuel consumption and emissions, anyway.

Both EVInc scenarios are built on the assumption that there is political will to foster the market penetration of (partly) electric vehicles. In the case of **EVInc1**, it is assumed that consumers are offered a subsidy for buying a PHEV or BEV. This measure does not change any vehicle characteristics, but it may affect fleet emissions indirectly through adjustments in the new fleet composition, which depends on annual costs of the vehicles.

It is assumed that the subsidy is of the flat-rate kind, i.e., 5000 €$_{2008}$ are payed for the purchase of any new PHEV or BEV. As assumptions on vehicle lifetime are the same for all vehicle types, each PHEV and BEV benefits from an annual cost reduction by the same absolute amount of roughly 560 €$_{2008}$ compared to BASE costs. The resulting annual cost differences to ICE can be seen from Table 4.15, fourth row[28]. Under EVInc1, PHEV are expected to cost less than ICE (roughly -200 to -400 €$_{2008}$ on an annual basis) in the BBN of experts 2, 3 and 6, while they are still more expensive for experts 5

[28]For the calculation of annual vehicle costs and assumptions on depreciation see Section 4.3.

and 7 (1920 €$_{2008}$ and 423 €$_{2008}$ p.a.). This leads to increased market shares of PHEV compared to BASE in the BBN of experts 2 and 3 (see Figure 4.42). For expert 2, the expected PHEV share triples to 55%, and for expert 3, it increases from 40 to 50%. Within the BBN of experts 1 and 4, no important shares of PHEV are assumed to be sold under any scenario. For the BBN of experts 6 and 7, no market share assessments are available.

Under EVInc1, the BBN of experts 1, 4, 5 and 6 show that BEV will cost up to 500 €$_{2008}$ less than ICE, annually, while the remaining three BBN propose that they will still be more costly. Compared to BASE, BEV market shares increase within the BBN of expert 2 (from 2 to 5%) and expert 4 (from 3 to 6%). For all others, BEV shares are as under BASE or not available.

Thus, EVInc1 fleet composition has changed in favor of PHEV in the BBN of expert 3, in favor of BEV in that of expert 4, and in favor of both in that of expert 2. The effect on fleet emissions, however, is minor. It is greatest in the case of expert 2, where a reduction in the 2030 new fleet emissions by 10 g to 113 gCO_2/km is brought about, compared to BASE. For expert 3, fleet emissions increase by 1 gCO_2/km, as his PHEV are more emission intensive as his ICE. For expert 4, expected fleet emission reduction amounts to 1 gCO_2/km.

In summary, promoting PHEV and BEV sales through a subsidy is little effective in regard to CO_2 emission reduction. First, even a subsidy of 5000 €$_{2008}$ for buying PHEV and BEV will not increase their market shares substantially within the BBN of many experts, all else equal. Second, considering only the BBN where increased PHEV or BEV shares come about, only in one case a perceivable reduction in the expected value of fleet emissions by 10 gCO_2/km results, while in two cases, only changes by $\pm$ 1 gCO_2/km are triggered.

A second policy which could be conceived for promoting PHEV and BEV shares is to limit prices for electricity used for mobility. In the BBN, a fixed price of 0.12 €$_{2008}$/kWh has been modeled within the scenario called **EVInc2**. Annual cost differences of PHEV and BEV compared to ICE are shown in the fifth row of Table 4.15. Absolute decreases in PHEV and BEV annual costs vary for the different BBN, as the amount of annual savings depends on the electric energy the vehicles consume per kilometer driven. The effect is that more energy-consuming vehicles are promoted more strongly than smaller or more efficient ones, a mechanism which may be detrimental to the aim of CO_2 emission reduction. For PHEV, annual cost reductions compared to BASE are between 107 €$_{2008}$ (BBN of expert 2) and 205 €$_{2008}$ (expert 6). For BEV, the range is from 110 €$_{2008}$ (expert 5) to 290 €$_{2008}$ (expert 3). Compared to the EVInc1 scenario just discussed, annual savings entailed by this incentive are much lower, namely less than half as much in almost all cases (and policy costs will be lower, as well).

Consequently, the effect on market shares and fleet emissions is even smaller than in the above case. For expert 2, PHEV reach an expected market share of 30%, nearly double that under BASE. For expert 3, the PHEV share increases by 2%. Expected BEV shares are up by 1% compared to BASE for two experts' BBN, resulting in shares of 3% for expert 2, and 4% for expert 4. For all other experts, market shares are either unaffected or unavailable. The fleet emission effect is nearly negligible: Within the BBN of expert 2, the expected value of fleet emissions drops by 4 gCO_2/km compared to BASE, and for expert 3, it increases by 1 gCO_2/km.

In sum, a substantial lessening of 2030 new car fleet CO_2 emissions through promotion of PHEV and BEV can not be brought about by any of the two measures discussed alone, but requires these car types to become less emission intensive, and their price to decline more strongly. At best, a price decline occurs autonomously, e.g., through falling battery prices, such that PHEV or BEV become competitive with ICE via market mechanisms.

While the effect of EVInc2 is small in the case modeled, where the fixed price for mobility electricity is the only change from BASE conditions, it could become more important if fuel prices increased drastically, or if consumers feared such increases. Then, buying a car that drives mainly or exclusively on electricity which can be bought at a fixed price could appear as an inviting alternative. This combination has not been included in the present analysis, but the effect of an increase in the fuel price to 1.75 to 2 €$_{2008}$ per liter has been analyzed within the **FP** scenario.

The effects on annual cost differences of PHEV and BEV to ICE can, again, be seen from Table 4.15 (sixth row). An increased fuel price makes it relatively more expensive to drive an ICE, or a PHEV in combustion engine mode. In most cases, FP PHEV and BEV annual cost differences to ICE are between those under the EVInc1 and the EVInc2 scenarios. For two experts (experts 3 and 7), in contrast, PHEV and BEV are relatively more expensive than or as expensive as under EVInc2.

The expected PHEV share more than doubles to 40% for expert 2, and increases by 2% to 42% for expert 3. BEV shares double to 4% for expert 2, and increase from 3% to 5% for expert 4. In all other cases, market shares are as under BASE or have not been given. As before, effects on fleet emissions are marginal; only for expert 2, their expected value decreases by 5 gCO_2/km.[29]

[29] In the FP scenario, as well as for the incentive scenarios EVInc1 and EVInc2, vehicle type

This reconfirms the conclusion that changes in single variables – such as a tightened EU car CO_2 emission limit, subsidized PHEV or BEV prices, reduced mobility electricity prices or increased fuel prices – are unlikely to invoke strong changes in the 2030 German new vehicle fleet composition or its emissions.

The Effects of Battery Technology Development

Two aspects of battery development have been explicitly modeled in the BBN: On the one hand, a reduction of battery prices, on the other hand, an increase in battery energy density. The first aspect can help reducing sales prices for PHEV and BEV, making them more attractive to consumers. The second aspect means that battery weight can be reduced, lowering the overall weight of vehicles and contributing to their energy efficiency. However, both effects can be contradicted by the tendency to increase battery power if prices decline or density increases in order to increase PHEV's electric range or BEV's range, or vehicles sizes. In the BBN, the **BAT** scenario has been implemented to examine these effects.

Annual cost differences of PHEV and BEV compared to ICE under BAT are displayed in Table 4.15 (second row). For expert 6, BAT PHEV and BEV annual cost increments are higher compared to BASE. The increase is roughly 140 and 300 €$_{2008}$ p.a., respectively. This is the case because expert 6 has rejected the higher price scenario for batteries, such that batteries are relatively cheap already under BASE and do not get less expensive under BAT, while overall battery energy increases. For all other six experts, PHEV and BEV cost less on an annual basis under BAT than under BASE. For PHEV, the range of annual cost reductions is 350 to 1600 €$_{2008}$, and for BEV, it is 130 to 3400 €$_{2008}$ p.a. While under BASE, both PHEV and BEV are more expensive on an annual basis than ICE in all BBN, the BAT expected values of PHEV and BEV costs are lower than those of ICE costs in the case of two experts, each.

Apart from costs, a second important characteristic of 2030 PHEV and BEV that depends on improvements in battery technology is their (electric) range. As it is assumed that PHEV and BEV batteries are fully charged once a day, their daily electric ranges depend on the capacity of the battery. Table 4.17 presents electric ranges for PHEV in its upper panel, and for BEV in its lower panel. For comparison, electric ranges are given for the BASE scenario, for the

emissions are unchanged compared to BASE. Changes in fleet emission are only brought about through fleet composition. The only exception is the reaction of fuel consumption to the FP scenario in the BBN of expert 7, which occurs because ICE and PHEV fuel consumption is determined through an optimization routine.

Table 4.17: PHEV and BEV 2030 Electric Ranges under BASE, BAT and LowC (km)

	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Exp. 7
BASE		55	58		194	129	50
		±24	±22		±0	±65	±0
BAT		64	73		194	150	50
		±29	±36		±0	±59	±0
LowC		67	84		194		
		±32	±38		±0		

	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Exp. 7
BASE	100	152	125	113	150	132	350
	±0	±56	±44	±32	±0	±42	±29
BAT	100	301	200	124	150	185	350
	±0	±91	±65	±50	±0	±54	±29
LowC	100	204	170	129	150		
	±0	±90	±66	±46	±0		

The tables display experts' expected values ± one standard deviation for 2030 PHEV (upper table) and BEV (lower table) electric ranges under different scenarios.

BAT scenario discussed in this section, and for the LowC scenario. For all other scenarios, ranges are as under BASE.

Under BASE, expected values for PHEV electric ranges spread from 50 to 194 km for the five experts who have considered PHEV. Under BAT, the interval is the same. The BBN providing the extreme assessments belong to the same experts under BASE and BAT (lowest estimate: expert 7; highest estimate: expert 5), and do not yield changes in electric ranges. For all other BBN, the electric range of PHEV under BAT is increased by roughly 20% compared to BASE. BBN can be divided into two groups; the first one contains those of three experts (experts 2, 3 and 7) which yield PHEV electric ranges of about 50 to 70 km under BAT (50 to 60 km under BASE), and the second one consists of two BBN (those of experts 5 and 6) which produce larger electric ranges of 150 km and more under BAT (130 km and more under BASE).

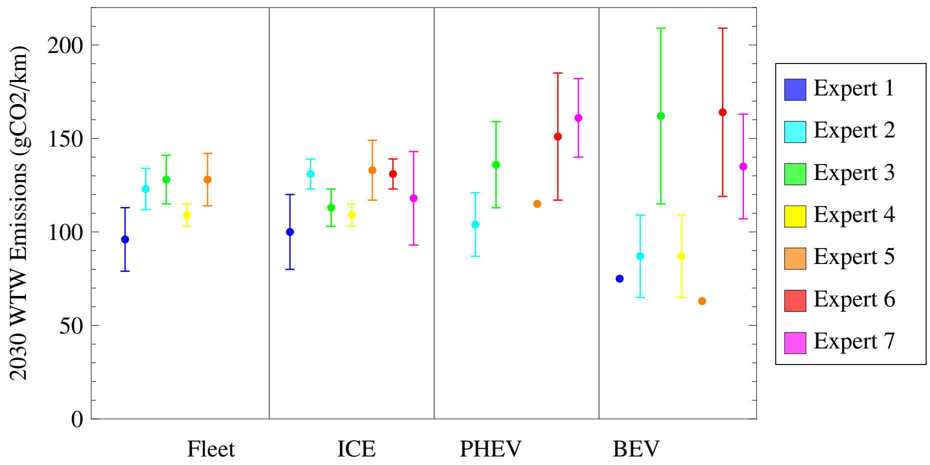
For BEV, electric ranges are more important than for PHEV. Thus, many experts imagine BEV electric ranges to be larger than those they have assigned to PHEV. However, one BBN (that of expert 5), which proposes the largest range of 194 km for PHEV, shows that BEV only cover 150 km with one charge of the batteries. The interval of BBN outcomes is 100 to 350 km of BEV range, again under BASE as under BAT. While for three experts' BBN (experts 1, 5 and 7), BEV range is unresponsive to improvements in battery technology, for the remaining four (experts 2, 3, 4 and 6) it increases up to double from BASE to BAT. Under BASE, six out of the seven experts' BBN give expected BEV ranges of 100 to 150 km, but only three of them stick to this range under BAT, while the other four give larger ranges of around 200 (two BBN), 300, and 350 km.

For assessing the usefulness of BEV, their ranges have to be compared to the distances drivers cover in a day. From the data given in Section 4.2.4, it can be seen that only 11% of German car drivers cover distances of more than 100 km a day. Thus, even the BEV with the smallest range of 100 km would be sufficient to cover the daily ranges driven by 90% of drivers. In regard to PHEV, it can be derived that even the lower PHEV electric ranges of little more than 50 km would suffice for covering the complete daily range of 70% of car drivers, and the larger ranges of 130 km and more would suffice for covering the distances driven by nearly 90%. Still, for PHEV, this aspect is much less crucial because additional distance can always be covered in ICE mode.

Under the BAT scenario, market shares of PHEV and BEV can increase compared to BASE because of decreases in annual costs, and increased ranges in the case of BEV. The expected sales shares of the different vehicle types have been displayed in Figure 4.42. As can be seen, the effects of the BAT scenario on market shares are similar to those encountered under EVInc1. The BBN of expert 2 yields a large increase of the PHEV share from 17% under BASE to 55% under BAT, and an increase of BEV sales by 1 percentage point to 3%. For expert 3, PHEV sales increase from their BASE value of 40% to more than 50%, and the BEV share doubles from 2 to 4%. In the BBN of expert 4, the BEV sales share doubles from 3 to 6%. For all other experts, market shares do not change or are missing.

In regard to emissions, different impacts convene under BAT. As under the EVInc scenarios, there are changes brought about by an altered fleet composition. In addition, the BAT scenario can also cause changes in the emissions of BEV and PHEV per kilometer, while ICE emissions remain unaffected. Figure 4.43 shows expected values $\pm$ one standard deviation for CO_2 emissions of the 2030 new vehicle fleet and the different vehicle types. The upper panel displays them under BASE and has been included as a point of reference. The lower panel shows emissions under BAT. It can be seen that ICE emission expectations are the same under BAT as under BASE. For PHEV, expected emissions

BASE:



BAT:

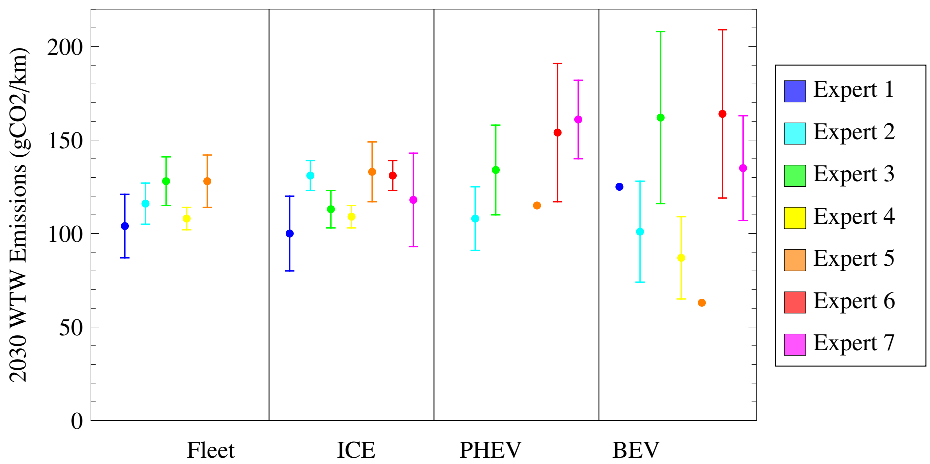


Figure 4.43: 2030 German New Vehicle Fleet and Car Type CO_2 Emissions under BASE and BAT (Error Bars)

The figure shows the experts' expected values for 2030 German new vehicle fleet and car type CO_2 emissions (WTW) under the scenarios BASE and BAT with error bars of one standard deviation. Both scenarios could be run in the BBN of all experts, but fleet emissions are available only for experts 1 throughout 5.

have changed slightly for three experts. The BBN of experts 2 and 6 propose them to be a little higher under BAT than under BASE (+4 and +3 gCO_2/km), while that of expert 3 suggests them to be reduced by 2 gCO_2/km. These changes are relatively small, and do not alter the overall picture. By and large, in the BBN of experts 2 and 5, PHEV emissions are lower than ICE emissions, while the BBN of experts 3, 6 and 7 put more weight on PHEV emissions higher than ICE emissions.

The BBN of two experts yield changes in BEV emissions under BAT compared to BAU. For all other experts, BEV emissions do not change. For expert 1, the expected value of BEV emissions increases by two thirds to 125 gCO_2/km under BAT, and for expert 2, it increases from 87 to 101 gCO_2/km. In the case of expert 1, this means that BEV, which are relatively low emitting vehicles compared to ICE under BASE, become relatively high emitting ones under BAT. For all others, relations stay unchanged, i.e., BEV are expected to emit less than ICE by experts 2, 4 and 5, and more than ICE in the view of experts 3, 6 and 7.

In almost all cases where a change in PHEV or BEV CO_2 emissions is brought about by the BAT scenario compared to BASE, the direction is towards higher emissions. In the BBN of expert 1, the strong increase in BEV CO_2 emissions under BAT is a direct consequence of his BBN specification. Instead of giving conditional probabilities for BEV energy consumption, he stated that 2030 BEV would be designed to cover a 100 km range with 100 kg of the batteries then available. Thus, his BBN does not offer the possibility of, e.g., increasing BEV range in case batteries improve, but an increase in specific battery energy leads to a higher energy consumption per kilometer, and thus directly to higher emissions.

In the BBN of expert 2, both PHEV and BEV have increased emissions under BAT. Both vehicle types are equipped with a heavier battery containing more energy than under BASE, and both consume slightly more energy (an additional 1 to 2 kWh/100km) in electric mode than they do under BASE. Regarding PHEV, under BAT, the electric range is extended and a higher share of the daily driving distance is covered in electric mode (62% compared to 58% under BASE). PHEV energy consumption in electric mode, combined with the relatively high-carbon electric energy mix assumed under BAT, results in PHEV emissions in electric mode higher than in combustion engine mode, and thus the higher share of electric propulsion adds to the increase of emissions under BAT in the BBN of expert 2.

Similar effects are behind the increase of PHEV emissions in the BBN of expert 6, as well. Although his PHEV carry less battery weight under BAT than under BASE, their energy consumption is increased slightly (from 24.7 to 25.4 kWh/100km), and the increase of PHEV electric share from 80 to 85% also drives towards higher PHEV emissions than under BASE. The BBN of expert 3 is the only one where PHEV emissions are reduced under BAT. Although more battery energy is installed than under BASE, the battery weighs considerably less (175 instead of 240 kg), and energy consumption is reduced by 1 kWh to 23 kWh/100km.

The overall effect of favorable battery development on the outcomes from single experts' BBN in regard to 2030 new fleet emissions can be seen from the 'fleet' panels in Figure 4.43. For expert 1, the expected value of fleet emissions has increased by 8 gCO_2/km, and for expert 2, it has decreased by 7 g (with unchanged standard deviations). For the other experts, the BAT scenario does not affect fleet emissions. For expert 1, the increase has been brought about by the increase in BEV emissions, while market shares have remained unchanged. For expert 2, in contrast, PHEV and BEV market shares have increased considerably. Although both PHEV and BEV emissions have augmented, they are still below ICE emissions, such that the overall effect of BAT is a reduction in emissions. For experts 3 to 5, the combined effects of adjusted market shares and car type emissions do not affect 2030 new fleet emissions. For experts 6 and 7, no market shares are given, such that no fleet emissions can be calculated. However, it can be said that no changes in car type emissions have occurred, and that fleet changes could only come about through adjustments in market shares.

In Figure 4.36, the expected values for 2030 new vehicle fleet emissions over all experts' BBN and different scenarios have been summarized. For the BAT scenario, it can be seen that they cover a higher sub-range of BASE expected values, extending from 104 to 128 gCO_2/km, whereas the BASE interval starts from 96 gCO_2/km. As a conclusion, it can be said that according to the experts, it is unlikely that favorable battery development will cause a decrease in emissions. However, two experts agree that it could support or evoke high PHEV market shares of more than 50%, and three think that BEV sales could be fostered by battery development, but with a still very low share of 6% at most. Such an increase in PHEV and BEV market shares may be detrimental for the aim of emission reduction. When combined with a massive extension of the share of renewables in the energy mix, however, CO_2 emission reductions could be achieved.

4.6 Outcomes on Subject and Methods and their Evaluation

There are two kinds of outcomes from the present study, one of them relating to the subject chosen, the other one to the method used. First, the BBN has been built in order to address a number of research questions regarding the subject of German new passenger car CO_2 emission development. Answers to these questions are one important kind of result, and will be summarized in the first part of this section (Section 4.6.1). A subsequent section then relates these findings to literature (see Section 4.6.2).

Second, an innovative approach has been used that combines the method of BBN with expert elicitation in order to derive expectations on future developments. Thus, a second kind of results concerns the validity and viability of these methods. How appropriate has it been to apply this approach to the questions at hand, what are its advantages and shortcomings, and what improvements can be proposed? These points will be addressed in the third part of this section (see Section 4.6.3).

4.6.1 Answering the Research Questions

In this section, answers will be given to the three research questions which have guided the present investigation.

4.6.1.1 How much CO_2 will the 2030 German new car fleet emit on average, and how can emissions be reduced?

The central question the BBN structure was designed to examine is how much CO_2 the 2030 German new car fleet will emit on average, and how emissions can be reduced. A baseline scenario (BASE) was defined to analyze the 'autonomous' development of fleet emissions in the absence of any further measures. Then, different other scenarios were implemented in the BBN for examining the effects of changes in policies, technology, and other parameters.

The experts' BBN show that under the baseline scenario, CO_2 emissions of the 2030 German new passenger vehicle fleet will be significantly lower than in 2008. The expected values of 2030 new vehicle fleet emissions range from 96 to 128gCO_2/km well-to-wheel (WTW)[30] for the different experts' BBN, which is 50 to 65% of 2008 new fleet emissions. Most of the networks show that ICE are likely to be the dominant vehicle type in 2030. Four out of the five completely

[30] Within this thesis, all emissions are given as well-to-wheel figures, i.e., they include aggregated emissions over the life cycle of fuel and electricity.

specified BBN[31] assign expected market shares of 80 to 90% to ICE, while one BBN raises the expectation that there will be roughly 50% of ICE and 40% of PHEV. Thus, in most BBN, emission reductions under BASE will be brought about predominantly by reductions in ICE fuel consumption, expected values of which range from 3.5 to 4.6 l/100km, resulting in emissions of roughly 100 to 130 gCO_2/km WTW.

The new car fleet emission effects of different measures such as a tightening of the EU car CO_2 emission limit, an increase of the share of biofuels, or an increase of renewable energies in the electricity mix have been analyzed within the BBN. While for each of these measures, at least some of the BBN suggest that fleet emissions will decline, there is no agreement on the degree of emission reduction or even on the most effective measure (see Table 4.18 for a summary of expected emissions under different scenarios). However, when all three measures are combined, as modeled under the RBC scenario, assessments converge and all BBN demonstrate reasonable certainty that 2030 WTW German new vehicle fleet emissions can be reduced to 100 gCO_2/km, at most, which is roughly half of the emissions of the 2008 new vehicle fleet. Expected values range from 40 to 50% of the 2008 German new passenger vehicle fleet's well-to-wheel emissions.

The low CO_2 (LowC) scenario has shown that fleet emissions can reach an even lower level than induced by the RBC scenario. Within this scenario, the BBN has been run in a bottom-up manner, fixing the lowest possible fleet emissions for each BBN. Two experts' BBN allow to drive down fleet emissions to roughly 20 and 30% of 2008 new fleet emission, respectively. This is reached by reducing ICE fuel consumption to extremely low levels (1.2 and 1.8 l/100km, on average). In a third BBN, emissions can be reduced to about 40% through a mixture of adjustments, including decreased PHEV energy consumption in electric mode, and reduced fuel consumption of both PHEV in combustion engine mode and ICE. Two further BBN do neither allow for very low levels of ICE fuel consumption nor for important shares of PHEV and BEV, such that fleet emissions can not be lowered beyond roughly 45% of 2008 new vehicle emissions. In the remaining two BBN, no fleet emissions can be calculated due to missing sales share estimates. While the LowC scenario shows that very low emissions are technically feasible in the view of many experts, they can not be triggered by the policy measures or technology development options implemented in the BBN, alone. However, such extreme emission reductions could be reached in case of a strong commitment of OEM to reducing emissions to their minimum, e.g., if driven by consumer demand.

[31] Two further BBN are incomplete, as the respective experts did not give sales share estimates.

In the current public discussion, BEV are often assumed to be low-emitting vehicles. This is not necessarily true under present circumstances. Under the BASE scenario, where today's electricity mix is used and combined with energy consumption figures as elicited from the experts, expected emissions of 2030 BEV range from 60 to 160 gCO_2/km for the different BBN, compared to 100 to 130 gCO_2/km for ICE. Thus, BEV emissions may be higher or lower than ICE emissions. Three out of seven BBN propose BASE BEV emissions to be higher than ICE emissions. For PHEV, a majority of three out of five BBN (two experts have eliminated PHEV from their networks) yield the result that they will emit more than ICE under BASE circumstances, and expected values range from about 100 to 160 gCO_2/km. Under the REN scenario, the share of renewable energies in the 2030 electricity mix has been increased to roughly 65%, compared to 10% under BASE. While this measure alone only has a small impact on 2030 fleet emissions, it is helpful in reducing PHEV and BEV emissions: The expected values of BEV CO_2 emissions drop to 30 to 80 gCO_2/km (15 to 40% of 2008 new fleet emissions). PHEV emissions are 60 to 100 gCO_2/km (30 to 50%). Thus, all BBN which include these vehicle technologies suggest that under REN, both BEV and PHEV will emit less CO_2 per km than ICE, thus they will be relatively low-emitting vehicles. Four out of seven BBN also propose that BEV will be very low-emitting vehicles under these circumstances, with expected emissions between 30 and 50 gCO_2/km, i.e., 15 to 25% of the emissions of the average 2008 German new vehicle. Thus, with a strongly increased share of renewable energies, BEV and PHEV can contribute to emission reductions, if meaningful shares of them are sold. But if electricity carbon content stays at current levels, roughly half of the experts think that BEV and PHEV will emit more than ICE and are no option for lowering car CO_2 emissions.

Table 4.18 summarizes 2030 WTW German new car fleet emissions and relates them to the emissions of the 2008 fleet. It includes, among others, quantified fleet emission estimates for the scenarios just discussed, namely BASE, the two scenarios leading to the strongest emission reduction over all experts, RBC and LowC, and the REN scenario. The intervals given comprise the available assessments of all experts.

4.6.1.2 What is the impact of certain alternative regulations?

A second research question addresses the impact of regulations. Two types of policies have been explicitly modeled in the BBN – a EU car CO_2 emission limit (Cpol scenario), and German incentive policies for promoting PHEV and BEV (EVInc1 and EVInc2).

Table 4.18: 2030 WTW New Car Fleet CO_2 Emissions under Different Scenarios

Scen.	Exp. Values (gCO_2/km)	Share of 2008 Emissions (%)	One sd Interval (gCO_2/km)	Share of 2008 Emissions (%)
BASE	96 – 128	50 – 65	80 – 140	41–72
Cpol	92 – 120	47 –62	69 – 137	35–70
REN	90 – 122	46 – 63	73 – 136	37–70
BF	88 – 120	45 – 62	73 – 132	37–68
RBC	80 – 96	40 – 50	60 – 100	31–51
LowC	35 – 85	18 – 44	30 – 90	15–46

First column: Range of expected values of 2030 WTW German new vehicle fleet emissions over experts 1 throughout 5 (experts 2, 3 and 5 for Cpol); second column: 2030 WTW German new vehicle fleet emissions as a share of the corresponding emissions of the 2008 new fleet (195 gCO_2/km); third column: Range of expected values of 2030 WTW German new vehicle fleet emissions $\pm$ one standard deviation over experts 1 throughout 5 (experts 2, 3 and 5 for Cpol); fourth column: One sd range as a share of the corresponding emissions of the 2008 new fleet (195 gCO_2/km).

The Cpol scenario aims at driving down emissions by providing a strict European car emission limit. For the three BBN where fleet emissions can be determined and Cpol can be implemented, it leads to reductions in the expected value of 2030 new car fleet CO_2 emissions by 8, 19 and 31 g/km compared to BASE, which corresponds to emission reductions by 6 to 25%. Two further experts have not provided fleet estimates, but the effect of Cpol on ICE emissions can be determined. In both BBN, they decline by 53 gCO_2/km, which is a reduction by 40 and 45% of BASE ICE emissions, respectively. In contrast, two experts attribute no impact to the Cpol scenario. One of them thinks that its impact is minor, compared to the pressure exerted by international competition, and the other one points out that the EU regulation was already decided upon so that no different scenarios could be applied. All in all, the effect of Cpol on CO_2 emissions is disputed among experts and ranges from inexistent to major. Due to the assessment as an important measure for emission reduction according to some BBN, Cpol is part of the integrated emission reduction scenario RBC which has been discussed above.

Further scenarios for reducing emissions which could be triggered through policy include an increased use of renewable electricity (REN scenario) or biofuels (BF). While it may be more likely for high renewable energy and biofuel quotas as modeled in those scenarios to be realized by 2030 in case they are supported politically, they could, in principle, also come about autonomously.

REN reduces emissions from PHEV and BEV considerably, but the effect on the overall fleet is small (2 to 6 gCO_2/km) in all but one BBN, where a reduction by 20 gCO_2/km occurs compared to BASE. This is due to the small role PHEV and BEV play in the 2030 new car fleet compositions resulting from most BBN. BF decreases emissions of ICE and to some degree PHEV. The overall effect on 2030 new vehicle fleet emissions is assessed to be a reduction by 8 to 12 gCO_2/km compared to BASE. The range of expected values of fleet emissions is roughly 90 to 120 gCO_2/km for each of the two measures, thus a less than 10 gCO_2/km shift from BASE or a less than 5% emission reduction based on 2008 has occurred (for the details, see Table 4.18).

Furthermore, two regulations have been considered for promoting the share of PHEV and BEV in the 2030 new vehicle fleet. Under the scenario EVInc1, a 5000 €$_{2008}$ subsidy is offered to every consumer who buys a new PHEV or BEV. Although this reduces vehicle costs and makes it cheaper for consumers to buy and drive a PHEV or BEV than an ICE in a majority of BBN, PHEV and BEV sales shares increase only within two BBN, each. While PHEV become the dominant vehicle type within two BBN, with sales shares of 50 and 55%, BEV shares only go up to 5 and 6%. In regard to emission reduction targets, the policy EVInc1 alone is little helpful. Within one BBN, fleet emissions decrease by 10 gCO_2/km; within the others, there are no significant changes. EVInc2 is a second incentive policy for PHEV and BEV, where the price for mobility electricity is fixed to a low level. Annual cost reductions caused by this measure are much lower than under EVInc1, and consequently, PHEV and BEV sales share increases are smaller. No important effects on fleet emissions result. Thus, both EVInc policies are not recommendable, as they do not even guarantee that their direct aim, the increase of PHEV and BEV sales shares, can be reached. Only two BBN show that PHEV or BEV shares will increase, respectively, under such policies. Moreover, as pointed out above, in a WTW perspective PHEV and BEV do not necessarily emit less CO_2 than ICE. Thus, without further measures, promoting their market shares might be detrimental in regard to CO_2 emissions.

4.6.1.3 What is the impact of selected technological advancements?

A third research aim was to assess the effects of technological development within the BBN. Battery development was chosen as a suitable candidate, both because of its vital importance for the market chances of BEV (and to a lesser degree PHEV), and because the current state of batteries leaves room for improvement. Two aspects of battery development were explicitly modeled, namely a decline of battery costs, and an increase in battery energy density.

Favorable development states for both were included into the BAT scenario. In this paragraph, BAT impacts on the costs, ranges, sales shares and emissions of PHEV and BEV will be summarized.

For understanding the effects of favorable battery development, it is helpful to know what PHEV and BEV vehicle characteristics experts had in mind when making their assessments. Their images of PHEV diverge strongly: Two experts think that they will not play a role at all in the 2030 German new car fleet. Two experts imagine PHEV as large, heavy cars designed for long-distance driving with up to 200 km of electric range and a full-fledged combustion engine, whereas one thinks they will be rather small, light vehicles with downsized ICE. Two experts did not describe their image of 2030 PHEV.

In contrast, a majority of four experts thinks of BEV as relatively small cars used as city or commuter vehicles. Three of them explicitly assigned BEV ranges between 100 and 150 km with one charge. Two pointed out that battery weight was limited to 100 kg or 200 kg, respectively, and one said they would offer seats for one or two persons, only. Two more experts could imagine BEV to travel longer distances and claimed that they would sell better if they allowed for ranges of 200 to 500 km. One expert said that BEV needed to offer a range of 300 to 400 km in order to be sold.

For the different experts, under BAT, PHEV annual costs are about 350 to 1600 €$_{2008}$ lower than under BASE, and BEV cost 130 to 3400 €$_{2008}$ less each year. Still, in the BBN of three out of five experts, PHEV cost 300 to 500 €$_{2008}$ more than ICE, annually, and within five out of seven BBN, BEV are roughly 350 to more than 1000 €$_{2008}$ more expensive than ICE. In contrast, PHEV and BEV are cheaper than ICE on an annual basis in two BBN, each.

PHEV BAT electric ranges are roughly 20% larger than under BASE for three out of five BBN, and do not change for the remaining two. Overall expected PHEV electric ranges are 50 to 200 km, under BAT as under BASE. BEV ranges are 100 to 350 km, again under BAT as under BASE, but within that interval, four out of seven BBN show that the BEV range will increase up to double under BAT compared to BASE. While range may be an important argument for consumer acceptance of BEV, even a range of 100 km, which is the lower boundary of assessments, suffices for covering the distances driven in a day by nearly 90% of car drivers in Germany.

Market shares react to the changes under BAT in a few cases, only. PHEV shares grow to more than 50% for the two BBN within which PHEV are less costly than ICE. BEV shares increase for three BBN, but from very low shares of 2 or 3% to shares of 3 to 6%. In the remaining BBN, no changes occur compared to BASE.

Similar to market shares, emissions react to BAT in a couple of cases only. In nearly all of them, emissions increase compared to BASE. For PHEV, changes in emissions are minor. Two BBN propose that they will be 3 to 4 gCO_2/km higher than under BASE and one suggests that they will be 2 g lower. For BEV, two BBN result in emission increases by 15% and by 66%, respectively, while emissions do not change for the others. The increases in emissions under BAT show that improvements in battery technology tend to be exploited for raising vehicle electricity consumption. In regard to overall fleet emissions, an increase by 8 gCO_2/km results in one BBN and a decrease by 7 g in another one, with no changes in all other BBN.

In sum, favorable battery development reduces PHEV and BEV vehicle costs but leaves them higher than ICE costs for a majority of BBN, and increases PHEV and BEV electric ranges for a majority of BBN. PHEV and BEV sales shares grow only in a minority of BBN, but PHEV become the dominant vehicle type (with sales shares of more than 50%) within two BBN. Effects on PHEV and BEV emissions occur in less than half of the networks, and drive in the direction of higher emissions. Fleet emission effects are minor. Thus, while the BAT scenario may increase PHEV and BEV market shares, it can have an unwanted impact on emissions, unless electricity carbon content is reduced, or PHEV and BEV energy consumption is lowered beyond the levels estimated by some of the experts, e.g., by designing them as small efficient vehicles.

In case the views of experts thinking of PHEV and BEV as large cars with major electric ranges realize, these cars are unlikely to make an important contribution to emission reduction, even if electricity is less carbon intensive than today. Under these circumstances, PHEV will be rather emission intensive vehicles, and due to the large batteries required, BEV will be too expensive to acquire meaningful market shares, even in case of favorable battery development.

4.6.1.4 Further Remarks and Discussion

Most BBN show that in 2030, ICE will still be the dominant vehicle type in the German new fleet. However, they suggest that 2030 new ICE will only cause half up to two thirds of the CO_2 emissions of today's new ICE. PHEV have high market shares only for few experts (two out of five), but in their view, they may become dominant under favorable conditions of battery development or incentive policies. BEV gain a 2030 market share of 15% in the view of one expert, but significantly less than 10% for all others, no matter what scenario. Under most of the scenarios considered, both PHEV and BEV emit more than ICE within at least some BBN. This is especially true for the BBN of experts who imagine them to be vehicles with the range and comfort of current ICE. Over all BBN, PHEV and BEV can be assumed to contribute to emission reduction with reasonable certainty only under REN, where electricity is generated predominantly from renewables.

These conclusions show that there is a certain 'stickiness' in the expectations of the experts. Most of them think that ICE will remain the dominant car type, and many think that vehicles will be difficult to sell unless they are similarly large, comfortable, and long-ranged as today's cars.

This said, the expectations regarding ICE emission reductions until 2030 seem astonishingly optimistic. In a first round of expert interviews which was carried out before building the BBN, technological options and their potential for car CO_2 emission reduction were examined. Looking back at the results from the first interview round presented in Chapter 3, it can be seen that experts interviewed at that stage assessed the emission reduction potential of combined efficiency measures to be between 10–20 and nearly 40%, and that of full hybridization between 10 and 40–45% (see Table 3.7).

Thus, if the expectations of the least optimistic first round experts become true, efficiency measures can reduce emissions by 10–20%, and full hybridization decreases them by another 10%. Assuming no intersections or trade-offs between the two groups of measures, with full implementation of both together, a 20–30% reduction can be achieved, which is still slightly less than the one third reduction in ICE CO_2 emissions resulting from the most pessimistic expert's BBN (hybridization steps are included into ICE technology in the BBN).

Even if expectations of the most optimistic first round experts realize, neither efficiency measures (with a reduction potential of 40%) nor full hybridization (40–45%) alone are sufficient for reaching an ICE emission reduction by half as resulting from the most optimistic expert's BBN under BASE.

The more optimistic results from the BBN approach, compared to the first round of interviews, can be partly explained by differences in the time frame (2020 for the first interview round, 2030 for the second), and partly by the fact that first and second round experts are not identical. Still, the impression remains that the present set of experts assesses ICE emission development in a way which requires considerable determination and devotion to emission reduction from OEM, or consumers willingness to buy smaller cars. ICE CO_2 emission development over the past few years has not shown this determination.

On the contrary, emission reduction obligations as discussed in the European Union have been fought against by the German car industry. The voluntary agreement of the European Automobile Manufacturers' Association (ACEA) and the European Commission to reduce emissions from new passenger cars to 140 gCO_2/km tank-to-wheel (TTW) by 2008 has not been met by German OEM. Average emissions of the 2008 German new car fleet were 165 gCO_2/km TTW (KBA 2010).

With the present method of expert-based BBN, results are subjective in that they aim at representing the individual expectations of experts.[32] As all experts asked to quantify BBN are representatives of car OEM, it is possible that results are biased and have been influenced by the experts' working environment, including company interests and policies and 'institutional assumptions' held within the OEM. With the present choice of experts, such biases could not be avoided. Actually, it was intended to grasp expectations held by experts within German OEM. However, it is impossible to differentiate in how far personal expectations or institutional expectations have shaped the results.

The present work was undertaken with the goal of examining options for reducing CO_2 emissions from the German car sector. As the focus was to analyze the effect of different technological pathways and to come up with probabilities that they will be taken, attention was drawn to the 2030 German new vehicle fleet. While a look at a new fleet is useful for deriving an assessment of technologies available twenty years from now, overall emissions from the automotive sector do not depend so much on a single year's new fleet, but on vehicle population. It takes quite some time for technologies and related emission levels to disseminate to the fleet as a whole. In 2008, there were 41 million passenger vehicles registered in Germany, with an average age of 8 years (KBA 2008, p.7). Only 3.1 million new passenger vehicles were registered in that same year (KBA 2009b, p.3). As discussed in Section 4.2.6, average useful life of passenger vehicles in Germany is roughly 12 years (KBA 2009a, pp.4f), and some are used much longer. This means that in 2030, a number of vehicles produced today will still be on the roads, emitting what 2010's vehicles emit. Thus, it must be cautioned against expecting a sudden reduction in fleet emissions from reductions in new fleet emissions. Once efficient technology is put on the market, there is a time lag of several years until old technology is replaced.

Apart from the diffusion of technology, there are more aspects which play a vital role for automotive sector emissions. To come up with an assessment of overall car emissions, fleet average emissions must be weighed with fleet size and driving profiles. Thus, the questions of how the fleet size develops, and of how much distance an average car covers in a year are of great importance. These

[32] Moreover, the decisions of the author of the present thesis in regard to BBN variables, their dependencies, possible states and the way they are quantified are likely to have an important impact on the outcomes.

factors, in turn, depend strongly on lifestyle aspects, settlement structures, and availability and quality of alternative forms of mobility, e.g., public transport, to name just a few aspects. All of them may undergo changes within the 20 years to come and thus add to the uncertainty contained in the present analysis. For example, is it thinkable that new mobility concepts make conventional cars less attractive? Or that options for electronic communication strongly reduce mobility demand? Or that new status symbols displace the car as a signal of social status? While few experts could imagine a major technological breakthrough in the twenty years to come, there might be room for a social breakthrough which would very much change the picture.

Apart from emissions caused during the use of vehicles, production emissions are important to get a complete life-cycle analysis. While in the present work, a life-cycle perspective has been applied to fuel and electric energy in order to be able to compare ICE and PHEV/BEV emissions, car production emissions have not been included into the model in order not to further complicate the issue. However, for a complete analysis, production emissions are important and need to be added. For example, in their life-cycle assessment of GHG emissions from PHEV in the US, Samaras & Meisterling (2008) find that PHEV with a range of 90 km emit about 180 gCO_2equ/km on a life-cycle basis, which includes roughly 35 gCO_2equ/km for vehicle production, and another 10 g for battery production (Samaras & Meisterling 2008, p.3172, Fig.1). This indicates that production emissions are not negligible, as in this case, they contribute roughly 20% of overall emissions for vehicle and 5% for battery production.

Special care should be taken in regard to emissions caused by battery production and recycling, as battery production needs to be scaled up compared to current use in case PHEV and BEV gain considerable market shares. Moreover, some attention should be given to the question of whether the resources needed for large-scale battery production are available in sufficient quantities, and what further emissions may accrue in the chain of their procurement.

Finally, the present approach focusses on Germany. This geographic limitation has been criticized by many experts in the first interview round, due to the global nature of the problem of car emissions. In regard to car sales, Germany is a mature and relatively small market compared to world demand. A reduction in German passenger vehicle emissions by some percentage points can easily be overcompensated by growing car demand and use in industrializing countries. Thus, reducing emissions from German vehicles is meaningful in regard to reducing global anthropogenic CO_2 emissions only if the technologies disseminate and help to reduce emissions from cars in other regions, as well. Given the role of the German automotive sector as an important export industry, such effects may occur. Still, this depends very much on the development of demand, and on factors influencing it, e.g., fuel prices.

Altogether, it has become clear that the present analysis is a piece of puzzle in a broader picture. It has the virtue of clarifying questions on the drivers of car CO_2 emission development, and it reveals the probabilities representatives of predominantly German OEM attach to different pathways.

4.6.2 Evaluating Subject Outcomes in the Light of Literature and Policy Goals

In this section, I relate the findings from the BBN analysis described above to projections of vehicle development and GHG emissions for the decades to come and to explicit policy goals. Abundant literature exists which discusses options for passenger car GHG emission reduction, treating different technologies and relating to geographical scales from national to global. The following paragraphs discuss a number of exemplary studies, but can not be said to be exhaustive. Given the wealth of existing studies, no complete literature review was aimed at, but an exemplary approach was taken.

In three subsections, the focus is first on 2030 CO_2 emissions of different vehicles types, then on their market shares, and finally on the impacts of regulation and technological development. Given the amount of aspects treated and literature cited, a short summary of the literature evaluation is provided in a fourth subsection.

4.6.2.1 2030 Car Type CO_2 Emissions

In the following, the BBN results regarding 2030 new vehicle type's GHG emissions are compared to what has been found in published studies. Successive paragraphs relate to the car types ICE, PHEV and BEV. There is also a brief note on HFCV, which have not been explicitly modeled in the BBN.

Internal Combustion Engine Vehicles
Experts' BBN show that much of the expected reduction of vehicle fleet emissions until 2030 comes from ICE. In Section 4.5.4.1, it has been concluded that under the baseline scenario (BASE), expected 2030 WTW ICE emissions range from 100 to 133 gCO_2/km, which is roughly a 30 to 50% emission reduction compared to the 2008 new vehicle fleet. When considering additional measures, e.g., an increased share of renewables in the electricity mix, a larger share of biofuels in the fuel mix, or a strict EU car CO_2 emission regulation, emissions can be further reduced. The combination of all three measures, modeled under the RBC scenario, reduces expected 2030 ICE emissions by 50 to 70% in regard

to 2008 new fleet WTW emissions for the different BBN. These findings will now be contrasted with the outcomes from different studies. Most studies use tank-to-wheel (TTW) figures, which is not a problem as long as emission reductions are given as proportions of current fleet emissions, because proportions are directly comparable over WTW and TTW approaches. Where absolute figures are given, a simple transformation needs to be applied which is explained later.

Shell (2009) has developed two scenarios for 2030 mobility in Germany. The first one extrapolates current trends (trend scenario), and the second one turns to a more sustainable development (alternative scenario). Under the two scenarios, 2030 gasoline vehicles consume 45 and 50% less fuel than in 2005. Diesel cars either have a 30% higher consumption than in 2005, or have returned to 2005 levels by 2030 after consuming more intermediately (Shell 2009, pp.6f). Thus, depending on the share of gasoline and diesel vehicles, 2030 new ICE fuel consumption changes for the trend scenario range from −45% to +30% compared to 2005, and are −7.5% under a 50/50 assumption. For the alternative scenario, the range is −50% to ±0%, and −25% in case gasoline and diesel vehicles have equal shares. In comparison to the BBN results, these emission reductions seem quite small. Even under the BASE scenario, 2030 fuel consumption resulting from the BBN is roughly 30 to 50% lower than in 2008 for the different experts.[33] ICE efficiency potential is thus assessed to be substantially smaller in Shell (2009) than what is suggested by the BBN. As Shell (2009, p.7) assumes market shares for alternative fuels and drivetrains to be moderate (see next section), it finds reduced fuel consumption in combustion engine vehicles to be the decisive point for car CO_2 emission reduction.

A second study that has been carried out by a consortium of car manufacturers, industry and (N)GOs has examined the future portfolio of powertrains in Europe (ECF 2010). It provides an assessment of the economics, sustainability and performance of ICE, PHEV, BEV, and HFCV in helping achieve the 2050 overall 80% decarbonisation goal set by the European Union. According to the study, this goal translates to a 95% decarbonisation of the road transport sector. ECF (2010, p.5) conclude that ICE have the potential to increase energy efficiency by 30% by 2020, but not much more afterwards, and can further reduce their emissions by using biofuels, availability of which may be limited (ECF 2010, p.5). This assessment is at the lower limit of ICE emission reductions estimated within the BBN.

Romm (2006) examines the advantages and shortcomings of different types

[33] As discussed in Section 4.5.3.1, the 2008 German new vehicle fleet average fuel consumption was 6.63 l/100km (KBA 2010). 2030 Baseline fuel consumption resulting from the different BBN is 3.5 to 4.6l/100km (see Table 4.13).

of alternative fuel vehicles (AFVs) on behalf of the US National Commission on Energy Policy. He concludes that for the near-term, efficiency improvements and hybridization will play the most important role in reducing car CO_2 emissions. By 2020, gasoline HEV are expected to be the dominant vehicle type, and to emit 30 to 50% less than current vehicles (Romm 2006, p.2609). This corresponds exactly to the degree of emission reduction resulting from the BBN for 2030 ICE compared to today's fleet under the baseline scenario. In the BBN, HEV are included into the ICE fraction, such that it can not be deduced in how far ICE emission reductions found within the BBN result from hybridization. Moreover, there is a ten years gap until German ICE have reached the same proportion of emission reduction which Romm (2006) expects a US HEV-dominated new fleet to realize by 2020. Given the much higher CO_2 emissions of US current new vehicle fleets compared to German ones, such a gap may be realistic.

Schallaböck et al. (2006, p.96) point out that new propulsion techniques are unlikely to contribute significantly to emission reductions in the foreseeable future. A combination of efficiency measures as discussed in Chapter 3 and alternative fuels is estimated to allow reducing the emissions of current standard vehicles by more than 50% (Schallaböck et al. 2006, p.77). The technical feasibility of such a strong cut in ICE emissions is supported by the BBN analysis. Under the LowC scenario, which forces the BBN to produce minimal feasible emissions, 2030 new ICE emissions of 48 to 94 gCO_2/km result (see Figure 4.38 for 2030 car type CO_2 emissions under different scenarios). This corresponds to 25 to 48% of 2008 new fleet emissions (which, at this point, is pragmatically assumed to consist of ICE only). However, most BBN show that some measures are needed to drive ICE emissions towards their lower limit, as the baseline scenario does not cut emissions by half in most BBN. The RBC scenario suffices to bring 2030 new ICE emissions down to 59 to 101 gCO_2/km or 30 to 52% of 2008 new fleet emissions, i.e., roughly to the level proposed by Schallaböck et al. (2006).

Further studies exist which propose absolute emission levels to be reached by 2030. As such levels are usually given in terms of tank-to-wheels (TTW) emissions, roughly 18% of emissions have to be added to obtain well-to-wheel (WTW) figures comparable to those resulting from the BBN analysis, as explained in Section 4.5.3.1.

Under its basic scenario, the 'Institut für Energie- und Umweltforschung Heidelberg' (IFEU) estimates the 2030 new passenger vehicle fleet to emit an average 99 gCO_2/km TTW in the NEDC (IFEU 2005, p.15). The study assumes that the fleet is composed of diesel and gasoline fuelled ICE vehicles, only. The assessment of 99 gCO_2/km TTW translates into roughly 117CO_2/km WTW. Comparing this figure to the 2030 car type CO_2 emissions resulting from the BBN shown in Figure 4.38, it can be seen that it corresponds very well to the median assessment of ICE emissions under the baseline scenario. Under most other BBN scenarios, 2030 ICE emissions are lower.

Fontaras & Samaras (2010) analyze how the target of reducing European Union new car fleet emissions to 130 gCO_2/km by 2015 can be met. They find that substantial reductions in vehicle weight, tyre rolling resistance and engine efficiency are needed even for reaching the goal of 140 g set for 2008. For the 130 g limit, changes in fleet composition as well as in vehicle and powertrain technology are required (Fontaras & Samaras 2010, p.1827). The authors are sceptic in regard to the 2020 target of reducing emissions to 95 gCO_2/km, but propose mild and full hybrids for this purpose (Fontaras & Samaras 2010, p.1833). Other technologies are not discussed. There is a difference in time frame of 10 years, as the BBN analysis relates to the year 2030. At that point in time, BBN suggest that a 95 gCO_2/km TTW target, which translates into 112 gCO_2/km WTW, can be reached within the 2030 new car fleet by the combination of measures of the RBC scenario (see Figure 4.38). Interestingly, for ICE[34] alone, an EU 95 gCO_2/km WTW CO_2 emission limit as modeled under Cpol would suffice to reach the target, but in the overall fleet, CO_2 emissions are increased by PHEV and BEV.

McKinsey (2007) have calculated costs and CO_2 emission reduction potentials for a wide range of measures in Germany, including many measures in the transport sector. For passenger vehicles, they find that the most important emission reduction option is to optimize gasoline and diesel engines (McKinsey 2007, p.40). Although the analysis extends to the year 2030, costs and CO_2 emission reduction potentials of alternative propulsion technologies are not presented in the report. The authors point out that they had considered natural gas, hydrogen and the fuel cell (McKinsey 2007, p.42) (but not BEV), and point out that these alternative technologies were expected to provide significant emission reductions only at a later point in time.

The studies discussed put much if not all the burden of new fleet emission reduction until 2030 on ICE, which corresponds very well with the results from the BBN analysis. In regard to quantified ICE emission reductions, a minority of studies cited is less optimistic than the BBN (Shell (2009) and ECF (2010, p.5)), the majority of studies roughly supports the present assessment (Romm (2006), Schallaböck et al. (2006), IFEU (2005) and Fontaras & Samaras (2010)), and none of them is more optimistic. Thus, the present analysis can be said to

[34]In the BBN, ICE include mild and full hybrids.

provide ICE emission reduction assessments at the upper end of what is found in the literature.

Plug-In Hybrids

As discussed in Section 4.5.4.1 and as can be seeen from Figure 4.38, 2030 BASE PHEV expected emissions range from roughly 100 to 160 gCO_2/km for the different experts. This is a 17 to 47% CO_2 emission reduction compared to the average emissions of the 2008 new vehicle fleet. Under the REN scenario, a 50 to 70% reduction can be achieved.

Most studies on PHEV emissions I have found do not quantify PHEV emission reductions, but give relations. For example, ECF (2010, p.6) find that on the European market, PHEV reduce CO_2 emissions considerably compared to ICE, and should be employed especially for short trips or where biofuels are available (ECF 2010, p.6). This is in contrast to the findings from the BBN. While it is true that 2030 PHEV reduce emissions considerably compared to 2008 new fleet emissions, their record compared to ICE depends on the carbon footprint of the electric energy they use. Under the baseline scenario, ICE emit less; under REN, PHEV emit less; and under RBC, both cause similar CO_2 emissions. The use of biofuels as modeled under BF only offers a minor PHEV emission reduction in regard to BASE. This is due to the fact that PHEV complete a relatively large share of the distance they drive in electric mode.

In his US-based analysis, Romm (2006, p.2612) compares PHEV to present cars, and finds that PHEV emit substantially less GHGs, cause lower overall costs and offer a longer range, with much less infrastructure problems than other alternative fuel vehicles. This is supported by the BBN, where – in comparison to 2008 average vehicles – PHEV are clearly less emission intensive.

Shiau et al. (2009) analyze the economics and the environmental effects of PHEV with different battery sizes in the US. They recommend a policy strategy focussing on small-capacity PHEV which are charged frequently. They find that if charged with average current US electricity at least every 20 miles, they are less expensive and release less CO_2 than current HEV or conventional vehicles. At larger charging intervals or battery capacities, environmental and economic advantages gradually disappear. This relation can not be found in the present BBN, e.g., the PHEV with by far the largest battery capacity is one of the lower emitters[35].

Samaras & Meisterling (2008) provide a life-cycle assessment of GHG emissions from PHEV in the US. They find that PHEV with different electric ranges

[35]This can be deduced from Table 4.14, which includes PHEV battery costs proportional to battery capacity, and Figure 4.43, which shows emission estimates of the single experts' BBN.

(30, 60 and 90 km) emit roughly a third less CO_2 per kilometer than conventional vehicles at current US electricity carbon intensity (670 g/kWh, which is similar to the BASE value of 625 gCO_2/kWh). However, they do not emit much less than HEV unless electricity is strongly decarbonized. As the study relates to the US, where current average passenger car emissions are higher than in Europe, absolute numbers need to be considered for comparison. With current US electricity, all three types of PHEV emit 180 gCO_2equ/km on a life-cycle basis, i.e., including roughly 40 gCO_2equ/km for vehicle and battery production (Samaras & Meisterling 2008, p.3172, Fig.1). Thus, the figure to be compared to PHEV emissions under the baseline scenario of the present study is 140 gCO_2equ/km. As Figure 4.38 shows, this is very close to the median expert assessment for 2030 BASE PHEV emissions. However, PHEV considered in the BBN differ from those defined by Samaras & Meisterling (2008) in that they have electric ranges of 50 to nearly 200 km (see Table 4.17), and in that they are estimated to have the given characteristics by 2030.

In summary, BBN outcomes coincide with other studies in finding that 2030 PHEV will have substantially lower CO_2 emissions than today's conventional vehicles, and with the finding by Samaras & Meisterling (2008) on absolute emissions. However, their emission record in relation to 2030 ICE depends strongly on the set of measures taken until then, especially on electricity carbon content.

Battery Electric Vehicles

For BEV, findings on CO_2 emissions diverge strongly among experts. While some conceive them as small, low-emitting vehicles, others require them to be as large and long-ranged as current conventional vehicles, which leads to relatively high emissions. As has been shown in Figure 4.37, expected emission ranges of one standard deviation do not overlap for the two groups within the different scenarios. Thus, a large range of expected emission values of 63 to 163 gCO_2/km results under the baseline scenario. This is 32 to 83% of the emissions of the 2008 new vehicle fleet. Under REN, the range converges towards 30 to 78 gCO_2/km or 15 to 40% of current emissions. The large range of assessments is not unusual, as a look at published literature shows.

In their study on the future portfolio of powertrains in Europe, ECF (2010, p.6) find that BEV are suitable for smaller cars and urban driving, where they can achieve an 80% CO_2 emission reduction compared to today. Resulting emissions are at the lower end of the range of expected emissions of 2030 BEV under REN, and are not even covered by the expectations interval for BASE BEV emissions (see Figure 4.38).

Wietschel & Dallinger (2008, p.9, Fig.1) find that BEV emit 50 to 80 gCO_2/km when using today's German grid electricity, thus, they would emit substantially less CO_2 than conventional vehicles at current electricity CO_2 intensity. The authors argue that, even when using night marginal power, which typically comes from coal fired power plants, BEV CO_2 emissions still would not be higher than those of conventional vehicles. This assessment corresponds roughly with that of the experts who think of small, efficient BEV. Still, it is in the lower area of some of their one standard deviation intervals (see Figure 4.40).

In contrast, MacLean & Lave (2003, p.59, Table 8) find that for the US and Canada, global warming impacts of BEV are about the same as those of current standard gasoline ICE. This is even higher than any of the expected values resulting from BBN within which 2030 BEV are specified as rather long-ranged vehicles.

A global assessment of BEV emissions can be found in the World Energy Outlook 2010 (IEA 2010). It describes a scenario for stabilizing CO_2 concentration in the atmosphere at 450 parts per million of carbon dioxide equivalent, the '450 Scenario'. A further scenario used is the 'Current Policies Scenario', which assumes no change in policies as of mid-2010. Under the 450 Scenario, the power sector is assumed to be largely decarbonized by 2035, worldwide, and transport becomes the biggest emitter (IEA 2010, p.417). As the CO_2 intensity of power generation is low in this scenario (less than 150 g/kWh), emissions from electric vehicles are significantly lower than those from ICE vehicles using oil-based fuels (IEA 2010, p.432f). As Figure 4.40 shows, in the BBN this is true only for the group of BBN where BEV are small vehicles even under RBC.

Apart from the conception of BEV as either small city vehicles or as large and long-ranged, BEV emissions depend strongly on the carbon intensity of electricity. As it is not evident what energy BEV should be defined to use – e.g., energy with 'average' CO_2 content, as done in this study, marginal energy, or completely renewable energy – there is intensive political debate on how to account for BEV CO_2 emissions. The following studies give arguments for different ways of accounting.

In a study edited by the World Wildlife Fund Germany, Horst et al. (2009, p.32f) compare WTW emissions of conventional vehicles and electric vehicles for different chains of energy procurement. They find that electric vehicles are preferable in regard to the climatic aspect only if efficient battery types are used and electricity comes from low-emission sources, e.g., renewable energies or CCS power plants. Horst et al. (2009, p.34) point out that presently, marginal electricity comes from coal power plants which cause emissions of 900 to 1000 gCO_2/kWh. Thus, if electric vehicles were assumed to be powered by marginal electricity from the grid, they currently did not reduce but increase CO_2 emissions compared to average standard ICE vehicles. However, the authors also state that, as additional demand for electricity does not increase the number of emission certificates issued for electricity production under the EU Emissions Trading System (EU ETS), additional electricity could, by definition, be considered emission neutral (Horst et al. 2009, p.34). However, this conclusion would hold beyond 2030 only if emission caps for the electricity sector were not relaxed in order to accommodate for emissions caused by additional electricity production related to electromobility (Horst et al. 2009, p.36).

For estimating average carbon content of 2030 electric energy, a projection must be made which relates to the policy framework. In their energy concept for the years up to 2050, the German Federal Ministry of Economics and Technology (BMWi) and the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) set the aim for the share of electricity from renewable sources in 2030 to 50% (BMWi & BMU 2010b). In the present study, an even higher share of 65% was considered under the REN scenario as an upper boundary.

An earlier draft of the energy concept contained a quantitative assessment of future passenger car CO_2 emissions, which did not make it into the final version: With a BEV and PHEV market share of 80%, average CO_2 emissions of the 2040 new car fleet could be as low as 35 g/km BMWi & BMU (2010a, p.29). The discussion of whether a share of 80% PHEV and BEV in the 2040 German new vehicle fleet is a realistic target according to the BBN will be left to the following section. However, drawing overall fleet emissions down to 35 gCO_2/km is unlikely to be feasible without assuming electric vehicles to cause zero emissions. In August 2009, the German government has published its 'National Electromobility Development Plan' (Bundesregierung 2009), which formulates the goal that "Electromobility will make a significant contribution to climate protection targets."(Bundesregierung 2009, p.17) Additional electric energy demand in the mobility sector, it argues, will be met with renewable energies. "The prime source for electromobility will be current from variable renewable energies that cannot be used elsewhere as part of load management."(Bundesregierung 2009, p.17) Energy needed on top of what is available for load management reasons would also be provided by extended renewable supply.

With this line of argument, BEV (as well as PHEV in electric mode) can be treated as climate neutral. The overall new fleet CO_2 emission effect then depends on the share of EV, as well as on the effects this definition may have on ICE: Horst et al. (2009, p.8) suspect that if electric vehicles are treated as climate neutral, further efficiency improvement of conventional engines could be stopped. The introduction of zero-emission BEV would reduce the pressure to increase efficiency of conventional propulsion systems, assuming that fleet emission limits will be complied with (Horst et al. 2009, p.36). Thus, in case BEV take over the burden of emission reduction – be it due to actually very low BEV emissions or due to favorable accounting – the rather large emission reduction potential which exists for ICE, according to BBN outcomes, could well not be realized.

In conclusion, the assessments of BEV CO_2 emissions diverge strongly among the BBN as among published studies and policy papers on the issue. This is due, on the one hand, to different images of BEV as either smaller urban or larger long-ranged vehicles, which have very different levels of energy consumption. On the other hand, there is no objectively right way to measure EV CO_2 emissions, as the definition of mobility electricity carbon content is ambiguous and subject to policy decisions.

Hydrogen Fuel Cell Vehicles

In the BBN, HFCV were not explicitly modeled, due to the fact that the experts of the preparatory round of interviews (described in Chapter 3) did not expect them to have meaningful market shares in the nearer future. HFCV's market shares were included into the BBN category of 'other vehicles'. The experts who quantified the BBN did not criticize this approach. Here, two contrasting statements are included, to show that there is no consensus on the future role of HFCV. Romm (2006, p.2611) assembles critical statements in regard to HFCV, and says that it is unlikely that hydrogen vehicles will gain a significant market share by 2030. "Of all AVFs[36] and alternative fuels, fuel cell vehicles running on hydrogen are probably the least likely to be a cost-effective solution to global warming"(Romm 2006, p.2612).

In contrast, according to ECF (2010, p.6), HFCV are a possible low-carbon substitute for medium and large ICE vehicles in Europe, due to their performance, range, and refuelling characteristics. By 2030, they could reach emission reductions by 80% compared to today (ECF 2010, p.6). In terms of total costs of ownership (TCO), which includes the costs over the entire vehicle lifetime, they find that HFCV have similar costs as PHEV and BEV for medium-sized cars by 2030. In the largest car segments, HFCV are found to have a cost advantage compared to BEV and PHEV beyond 2030, and to be significantly more cost competitive than all other car types including ICE by 2050.

[36] AFVs is an abbreviation for 'alternative fuel vehicles'.

4.6.2.2 2030 Market Shares of the Vehicle Types

Apart from the GHG emissions different vehicle types cause, their market shares are decisive for overall fleet emissions. In this section, BBN results on 2030 market shares will be compared to findings in the literature.

BBN outcomes on vehicles types' sales shares in the 2030 German new fleet have been discussed in Section 4.5.4.3 and visualized in Figure 4.42. The great picture is that a majority of four (out of five completely specified) BBN under BASE and three BBN under more EV-favorable scenarios yield an ICE-dominated 2030 German new vehicle fleet with ICE market shares of 80% and more. However, one BBN exhibits a PHEV market share of 40% under BASE, and two BBN accord more than 50% of PHEV under BAT and EVInc1. BEV shares are 6% at most for four experts, and 15% for a fifth one. For the remaining two BBN, no sales shares have been specified. PHEV and BEV shares have been summarized in Table 4.16.

As vehicle types are complementary in fleet composition assessments, this section can not be strucutred analogously to the previous one. The first paragraph deals with qualitative assessments of ICE dominance, a second one describes and discusses quantified fleet composition estimates, and a third one deals with the German policy goals for the market penetration of electric vehicles.

Dominance of ICE

As the discussion in the previous Section has shown, many authors go conform with the finding from the BBN that ICE (including HEV, i.e., all degrees of hybridization up to the full hybrid, but with no charging from the grid) will be responsible for the largest part of emission reductions up to 2030. Apart from favorable assessments of ICE emission reduction potentials, in many studies this is linked to a forecasted dominant share of ICE in the 2030 new vehicle fleet. For example, IFEU (2005), Fontaras & Samaras (2010) and McKinsey (2007) have not even considered vehicle technologies other than ICE in their models or assessments, and Schallaböck et al. (2006, p.9) have pointed out that in the coming decades, gasoline and diesel vehicles are likely to continue dominating the car market.

The IFEU has developed a model describing motorized traffic in Germany, kilometers traveld, energy consumption and emissions, using scenarios for forecasting these items until 2030. The 2030 new passenger vehicle fleet considered within their model is composed of gasoline and diesel ICE only. They argue that it is unclear whether electric vehicles are going to make up for a relevant share of vehicle miles traveled in 2030 (IFEU 2010, p.56).

For the US and Canada, MacLean & Lave (2003) examine a wide range of fuel and propulsion systems that could be applied roughly up to 2030. They find that "Absent major technological breakthroughs, a doubling of petroleum prices, or stringent regulation of fuel economy or greenhouse gas emissions, the 2030 LDV[37] will be powered by a gasoline ICE."(MacLean & Lave 2003, p.5) This statement reconfirms the assessment published in Lave et al. (2000) that ICE and fossil fuels will stay the dominant fuel/propulsion system unless market conditions change strongly. MacLean & Lave (2003) are especially sceptic in regard to the technological and economic viability of BEV and HFCV. While they point out that cellulosic ethanol, fuels from natural gas, and HEV are attractive, they think that even the establishment of such technologies in the US and Canada depends on ICE showing no further efficiency improvements, or on rising conventional fuel prices (MacLean & Lave 2003, p.5).

These assessments support the present finding from most BBN that ICE will be the dominant 2030 new vehicle type. However, as they are qualitative in nature, no excact comparison can be made. Fleet composition assessments where electric vehicles are not even considered happen to assign a zero market share to them. This is much more pessimistic than present results for most BBN, as they suggest aggregated PHEV and BEV shares of 2, 12, 15, 19 and 42% under the baseline scenario, and of up to 60% under more favorable scenarios for single experts (see Table 4.16).

Quantified Fleet Composition Assessments

Apart from the above qualitative assessments, some quantitative forecasts exist. In its scenario analysis of 2030 mobility in Germany, Shell (2009) offers a quantified assessment of fleet composition. Under the trend scenario, the 2030 German new car fleet contains 20% of hybrids (i.e., HEV), 2.5% of electric vehicles (BEV), and 4% others (Shell 2009, p.6). Under the alternative scenario, hybrids make up for 50% of new cars, electric vehicles for 10%, and others for another 5.5% (Shell 2009, p.7). Thus, even under the more ambitious alternative scenario, the 2030 new fleet is projected to contain still more than 80% of conventional fuels and drivetrains (Shell 2009, p.7). In comparison to BBN outcomes, the Shell trend scenario assessment of 2.5% BEV is at the lower end of BBN expected values which range from 2 to 15%. In contrast, the alternative scenario share of 10% is more than the up to 6% shares four out of five BBN produce under the different scenarios (see Table 4.16). However, it is well within the range of the fifth assessment, which is 15% under any scenario.

Different scenarios on a global scale are provided by IEA (2010). Under the

[37]LDV is an abbreviation for Light Duty Vehicle.

World Energy Outlook's Current Policies Scenario, conventional ICE vehicles including hybrids still make up for nearly a full 100% of global passenger light duty vehicle sales by 2035, and electric vehicles gain only a negligible share. This is more conservative than the BBN assessments for Germany. Under the 450 Scenario, ICE including hybrids contribute nearly 60% of new vehicles, PHEV roughly another 30%, and electric vehicles some 7% (IEA 2010, p.431), which corresponds to a number of nearly 20 million electric vehicles sold in 2035 (IEA 2010, p.433). Three experts' BBN show a strong scepticism in regard to PHEV viability. Two of them do not even include PHEV, i.e., experts have assigned a close to zero share. For a third one, PHEV reach a 2030 sales share of 6% under BAU as well as under more favorable scenarios, which is much below the WEO estimate. In contrast, the PHEV shares within the remaining two BBN are much higher, at 50 to 60% under favorable scenarios. For BEV, the WEO estimate is slightly higher than those resulting from four BBN, and roughly half that of the fifth.

Wietschel & Dallinger (2008) provide an estimate which relates to PHEV and BEV shares in the overall fleet, which can only roughly be related to the 2030 sales shares provided by the BBN analysis. They consider two scenarios, which diverge, e.g., in regard to the assumptions on battery and oil price development. Under the 'Pluralism Scenario', the 2030 German vehicle fleet contains 3.5 million PHEV, and $160,000$ city BEV. Under the very optimistic 'Dominance scenario', it includes 11.5 million PHEV, $150,000$ BEV, and $160,000$ city BEV (Wietschel & Dallinger 2008, Figs. 4 & 5). For arriving at 3.5 million PHEV on German roads by 2030, roughly one in ten vehicles sold between 2020 and 2030 needs to be a PHEV (assuming that a good 3 million new vehicles will be sold in Germany every year between 2020 and 2030, and that no BEV is taken out of service during that period). Under BASE, this seems feasible within one BBN, and is likely to be exceeded in another one. For getting 11.5 million PHEV, roughly one in three vehicles sold from 2020 to 2030 needs to be one, which is likely to happen under BASE in one out of five BBN, and under the more favorable scenarios BAT and EVInc1 is likely to be overfulfilled within two BBN (see Figure 4.42 and Table 4.16). In both cases, a majority of three BBN estimate PHEV market shares to be too low for reaching such shares under any scenario. The BEV annual new fleet shares needed to achieve the absolute numbers given by Wietschel & Dallinger (2008) are around 0.5 and 1% of annual car sales from 2020 to 2030, which seems roughly compatible with the BBN results of three experts, and is likely to be strongly overfulfilled within two more BBN.

The following section will present the targets of the German government regarding EV market penetration, which are in-between those of the two scenarios described by Wietschel & Dallinger (2008).

German Policy Goals for EV Market Penetration

The 'National Electromobility Development Plan' of the German government (Bundesregierung 2009) sets the ambitious target for Germany to become the leading market for electromobility. The German Federal Government aims at having 1 million of electric vehicles on the road in Germany by 2020, and the somewhat less determined aim of "possibly reaching over five million" electric vehicles by 2030 (Bundesregierung 2009, p.17).

In their energy concept, the German ministries BMWi and BMU set a more ambitious goal of six million electric vehicles on the roads by 2030 (BMWi & BMU 2010b, p.24). As it can be questioned what exactly 'electromobility' refers to, e.g., whether or not it includes full HEV or HFCV, it is explicitly pointed out that "the National Electromobility Development Plan is concerned with battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV), including range-extended electric vehicles (REEV)."(Bundesregierung 2009, p.6) Still, it remains somewhat unclear whether the 1 million and 5 to 6 million targets for 2020 and 2030 are meant to include these types only, or whether they extend to two-wheeled vehicles (e.g., electric bicycles, Segways, etc.), microcars and HFCV mentioned earlier in the same paragraph (Bundesregierung 2009, p.5). For the present purposes, it will be assumed that targets refer to BEV and PHEV as defined within the BBN, summarized as electric vehicles (EV) in the following.

As the present BBN regard the 2030 new fleet, and the above targets concern the overall vehicle fleet in given years, a back of the envelope calculation is made to translate the policy targets into annual new fleet shares. As discussed in the previous Section 4.6.1, the German newly registered 2008 fleet consisted of 3.1 million vehicles. Under the assumption that the number of new cars registered annually will stay roughly constant over the next decade, about 30 million new vehicles will be sold from 2010 to 2020. If one million of them are to be electric cars, this amounts to an average share of 3.3% in each year's new fleet (assuming, for the sake of simplicity, that we start from zero electric vehicles in 2010, and that none are taken out of service during the decade in question). As the number of new electric vehicles registered in Germany in 2010 will be rather close to zero, a higher share will be required in a later year, and the same is likely to be the case for the next few years.

In order to reach the 5 to 6 million target, roughly another 5 to 6 million electric vehicles have to be put on the road in the decade from 2020 to 2030, as most electric vehicles which were new in the previous decade will have been taken out of service by 2030. Assuming that another 30 million new vehicles will be registered in Germany from 2020 to 2030, for reaching a target of 5 million, electric vehicles will need to contribute an average share of 16.6% of newly registered vehicles every year, and of 20% for reaching 6 million. As, again, this may be unlikely to be the case in 2020, the share then needs to be higher by 2030.

This rough assessment of an EV market share of at least 20% of electric vehicles necessary by 2030 can now be compared to the BBN outcomes. In the light of the present results (see Section 4.5.4.3 and Figure 4.42 for a presentation and discussion of sales shares), these aims look ambitious. As Table 4.16 shows, they are rather sure to be fulfilled only within the BBN of one expert, which yields a 2030 share of 43% of new electric vehicles, predominantly PHEV, even under the baseline scenario.

One further BBN produces a BASE share of 19% EV, again largely PHEV, which may or may not suffice for reaching the target, depending on by when shares rise to this level. However, this BBN yields 2030 EV shares of around 60% for both BAT and EVInc1, which indicates that more moderate rates of battery improvement or market incentives than modeled in these scenarios may suffice for raising the EV share considerably and reaching the policy target.

According to a majority of three out of five BBN, however, the goal will not be reached. They propose 2030 EV market shares of 3, 12 and 15% under the baseline scenario, and only the BBN with the smallest share reacts to battery improvement or EV incentives, doubling its EV share to 6%.

Interestingly, it is the assessment of PHEV market chances that is decisive for whether or not the goal of 5 to 6 million EV on German roads by 2030 is within reach. For both BBN which suggest it is, this is the case due to large PHEV sales shares, while the 2030 quotas of BEV are at 2% under BASE, and at 5% maximum under more EV-favorable scenarios. The remaining three BBN with quantified sales shares, where the aim can not be reached, propose very low PHEV market shares of zero or 6%, no matter what scenario. As BEV shares are relatively low for most BBN (2 to 6% for four BBN, 15% for the fifth one), large EV fleets can not be established relying on BEV alone, but PHEV are needed as a contributor.

4.6.2.3 Impacts of Regulation and Technological Development

In Section 4.6.1, the effects of alternative regulations as well as of battery development within the BBN have been analyzed. It has been found, e.g., that a stricter EU car CO_2 emission policy (Cpol) decreases ICE emissions in five out of seven BBN, in some of them strongly. Incentives for buying EV (EVInc1&2) have an impact on PHEV and BEV sales shares in two BBN, but do not drive down fleet CO_2 emissions.

For reaching the EU 2020 target of reducing car emissions to 95 gCO_2/km, Fontaras & Samaras (2010, p.1833) remark that "non-technological factors such as policy measures, incentives and consumer awareness may play an important role in accelerating the necessary development." The present results support the possible impact of policy measures, but suggest that incentives for buying EV of the kind modeled in the BBN are little helpful in regard to emission reduction.

According to BMWi & BMU (2010b, p.24), it is planned to decree a German labeling regulation for electric vehicles, which can then serve to draft privileged treatment, e.g., free parking space. The authors point out that such measures could provide incentives to buy electric vehicles. On the basis of the present analysis, it can not be said whether non-monetary incentives would play a decisive role. However, the present results go conform with BMWi & BMU (2010b) in a second point. The authors pressure towards a European regulation of car emissions beyond 2020 as a key driver for the market penetration of CO_2 efficient vehicles. Such an effect has been found within five out of seven BBN.

In their review of the progress OECD and European Conference of the Ministers of Transport (ECMT) countries have made in reducing transport sector CO_2 emissions, ECMT (2007, p.3) concludes: "Slowing the growth of transport sector CO_2 emissions would require more government action and an increasingly pro-active role from transport sector industries in improving energy efficiency." While the former point has been discussed above, the second one relates nicely to a finding deduced from the LowC scenario (see Section 4.5.4.1). BBN show that technically, 2030 new fleet emissions can be reduced to 35 to 85 gCO2/km, or 18 to 44% of 2008 new fleet emissions. While non of the modeled measures suffices for triggering a development which reduces emissions to their technical minimum, a pro-active role of industry would probably help.

Finally, battery development has been identified as a critical factor for the market success of electric vehicles. Both battery costs and specific weight currently poses problems to EV deployment.

In October 2010, an Audi A2 equipped with electric propulsion and a lithium-metal-polymer battery by the small company 'DBM Energy' traveled 600 km from Munich to Berlin without recharging, attracting much public attention. The construction of the vehicle was sponsored by the German ministry BMWi. According to Rudschies (2010), DBM has specified the battery to have a capacity of 100 kWh and a weight of 350 kg, and both the specific weight and volume of the battery were much better than those of current standard batteries (Rudschies 2010). However, Rudschies (2010) expresses some doubt regarding the potential of the battery to persevere long-term daily use, and mentions unsolved security issues regarding the technology employed. Moreover, the vehicle had disappeared for about half an hour several times during the test, and had not been inspected by a neutral institution.

The question of whether or not the DBM battery is a breakthrough in battery technology or a hoax can not be answered at this point. Evidently, a battery with a capacity of 100 kWh and a weight of 350 kg, thus, with an energy density of 0.29 kWh/kg, would be far beyond the development expectations discussed in Section 4.2.3.2, or the modeled scenarios of 0.12 and 0.2 kWh/kg. If such a battery became available for the mass market at a reasonable price, the present findings for PHEV and BEV ranges, costs, and areas of application could be strongly improved.

4.6.2.4 Short Summary of Literature Evaluation

As a lot of comparisons have been presented in this section, the following lists provide a quick overview on how the outcomes from BBN are positioned in comparison to published literature and policy aims.

In regard to car type CO_2 emissions, the following relations were found:

- The BBN assessments of ICE emission reduction potentials are at the upper end of what is found in the literature, but not out of range. The prevailing focus on ICE as the technology that will bring home the bulk of emission reductions is confirmed by many other studies.

- BBN findings on PHEV to have lower emissions than today's standard vehicles coincide with literature. However, due to divergent car configurations among experts as well as in the literature, and due to the strong impact of future energy GHG content, PHEV emissions are assessed very differently within different sources and are hard to compare.

- BEV emission assessments diverge extremely among experts' BBN, as they do in the literature. There is no objectively right way to quantify BEV emissions, as the question which energy they consume – average, marginal, or 100% renewable – is controversially debated.

- The BBN does not provide any quantification of HFCV emissions. In literature, such assessments are comparably widespread as for BEV.

As regards market shares, the comparison showed the following main points:

- Many studies assume or find ICE (including HEV) to be the dominant vehicle type in the 2030 German new fleet, which is often formulated qualitatively. This corresponds to the outcomes of a majority of BBN which, however, do not generally suggest that other vehicle types will have no significant shares.
- In comparison to quantified assessments of PHEV and BEV shares from scenario studies in the literature, the shares produced by the BBN tend to be higher than for the baseline cases, and lower than within very positive scenarios.
- The target of 5 to 6 million electric vehicles on German roads by 2030, set by the government, is without reach for a majority of three out of five fully specified BBN, clearly within reach for a forth, and possibly within reach for the fifth one.

A further point discussed in the literature and analyzed within the BBN is the impact of regulation on car CO_2 emissions, a comparison of which showed that:

- While no quantitative assessments could be found, different studies confirm the impact of a stricter EU car CO_2 regulation on ICE emissions found within five out of seven BBN.
- Beneficial effects of market incentives for EV on car CO_2 emission reduction could not be confirmed by the present BBN.
- The present investigation shows that a firm commitment of industry to reducing car GHG emissions could be very helpful in realizing further potentials, a finding that is supported by one review.

4.6.3 Evaluating the Method and its Present Application

The present approach is innovative in that it uses subjective probability assessments on future developments as an input to a Bayesian Belief Network. Many characteristics of BBN have proved advantageous for this approach.

With BBN, modeling tasks can be divided into several steps. BBN consist of a graphical model with a probabilistic model superimposed. This structure allows the modeling of general dependencies and their quantification to be carried out in separate steps, using diverse forms of input. In the present application, the graphical model was set up on the basis of the results from the first round of expert interviews presented in Chapter 3. In this process, interview results were combined with feedback from scientists and findings from literature. Then, for the quantification of conditional probabilities, a second round of expert elicitation was initiated, the outcomes of which have been presented in this chapter. In this series of interviews, experts were confronted with the structure of the BBN and asked to give their quantitative assessments. BBN allow to combine different sources of knowledge and to divide labor – features which have been exploited extensively. BBN have thus proven to be a useful tool for stakeholder-based science, because the concerns or the judgements of third parties involved in the issue at stake can be factored in, and their knowledge can be incorporated into the assessment.

Software offers implementation of fast BBN updating algorithms, such that at the end of an elicitation, the respective expert could be shown a compiled version of his quantified BBN. First results from the quantified models were directly fed back to the experts, and they were asked for a short critique. Now that the different BBN have been thoroughly evaluated, and some of them have been adapted after the interviews, it would be very interesting to organize a third round of interviews or discussions, where outcomes could be presented to the experts in greater detail. Their critique could be recorded and used for further adaptation of the networks. In this sense, BBN can be a core ingredient of an iterative, stakeholder-based science process.

BBN software also permits to update the beliefs about probabilities of the variables' states whenever new information becomes available. This quality was used for the scenario analysis performed. In 'what-if...' manner, BBN variables were set to hypothetical 2030 states, and the updated BBN were used to analyze the impacts of such conditions. This feature was employed for analyzing the outcomes of a set of scenarios on regulation, battery technology development, and fuel and electric energy carbon intensities. Moreover, BBN have the unique capability of permitting 'inverse' updating – they can learn from information entered in *any* of their nodes. Thus, in a further scenario, the node for 2030 new car fleet emissions was instantiated at its lowest possible level, and the experts' BBN were used to examine how very low emissions can be achieved. This feature is a main advantage of BBN compared to other methods, e.g., influence diagrams, and was fruitfully employed in the present analysis.

The questions of what new car types will be sold in 2030, what will be the state of their technology, and how much CO_2 they will emit depend on many factors the development of which is inherently uncertain, and answers can not be known today. In this situation, the basic idea was to use experts' subjective probabilities and compare them among each other in order to offer a range of informed judgements. Subjective probabilities are a valuable concept for analyzing and supporting human decision-making under uncertainty. However, their elicitation is demanding. It presupposes that interviewees are willing to reveal their assessments, and that they are ready to frame them as (conditional) probability distributions over different variable states. An expert's willingness or ability to do so may decline for events further in the future, and at some point, the exercise may collapse to pure guesswork. In this sense, the approach taken here was quite experimental. Before doing the interviews, I was not sure whether experts would accept the given questions and time frame as issues where they had a reasonably clear picture, or rather as questions where they could only guess. I was positively surprised by experts' readiness to participate in this study. While some of them were not content with parts of the model or the approach in general, most felt able to give a judgement. Many experts concentrated probability mass on few states, setting others' probabilities to zero, which shows that they were certain enough about their assessments to narrow down the ranges of possible states for some variables.

The need to proceed with elicitation within a reasonable timeframe constrained the number of variables probability distributions for which could be elicited. Moreover, to keep the size of conditional probability tables for each variable manageable, the number of variable states had to be restricted to a minimum. Therefore, first, only few impacts could be modeled explicitly, and there remain many implicit assumptions which affect the probability distributions experts have assigned, but can not be seen from the BBN. A given implicit factor can be very relevant for the assessment of one expert, and much less so for another one, or expectations on its development can vary strongly among experts, which makes it difficult to compare these assessments. Second, in order to reduce the number of states a variable can take while covering the whole range of possible values, large categories have been defined for a number of variables. This may impede the precision of results. For example, for 2030 BEV incremental annual user costs compared to ICE, which are modeled to influence BEV sales, three states were defined, one of which is 0 to 4000 €$_{2008}$. It is unlikely that consumers would mind paying, e.g., 1 €$_{2008}$ on top of annual ICE costs if they prefer a BEV, but an additional cost of 3000 €$_{2008}$ p.a. is more likely to prevent them from choosing a BEV. This example shows that too large categories can pose a problem within the present BBN.

Apart from the problem of large categories, discrete categories of any size generate discontinuities. For example, the impact of subsidies for buying PHEV or BEV depends on whether or not annual user costs pass the threshold towards a lower cost category. If they do, there can be a sudden jump to a higher sales share, depending on the node's conditional probability table given by an expert. These sudden reactions to incremental changes are unrealistic, but can not be avoided if discrete categories are used.

The subdivision of the continuous variable space into discrete states simplified elicitation considerably. Eliciting continuous distributions from experts is an intricate and time-demanding art, and it would not have been feasible to elicit continuous distributions instead of discretized ones for all expert nodes in the present BBN in useful time. Even if continuous distributions had been elicited, it would have been impossible to process them for computational reasons. Before compiling the BBN, probability tables need to be calculated for each node which contains an equation, and to this aim, nodes containing continuous variables need to be discretized into countably many states.

Moreover, despite of the restrictions I made concerning the number of variables and their states, the present BBN already exploits computational power of the software to its limits. In fact, a complete and fully specified BBN requires too much memory for compiling on a standard personal computer or laptop. For evaluating the BBN, I had to work with a special version of the software that does approximate inference based on sampling (instead of using the standard algorithm for compiling the BBN).

Once the BBN had been fully specified and compiled, a further unsolved issue was how best to present all the information they contain. There are seven different BBN, one for each of the experts, which contain a lot of information. Each BBN can be run under different scenarios, and probability distributions for each variable can be read off or exported. However, there is no satisfactory solution for displaying this information outside of the BBN software without losses. Furthermore, it is unclear whether the findings from the different experts' BBN should be aggregated for the purpose of presentation, as this deprives the reader of the chance to choose her own weighing scheme for experts' opinions.

In the present chapter, several ways of displaying BBN results have been tested. For the baseline scenario, the complete probability distributions of all experts have been presented together for central variables, both in order to demonstrate what information is actually contained in the BBN, and to give an impression of the uncertainty included in the experts' assessments. For a better overview, however, at most other points in the description, only expected values and standard deviations have been used. While this simplified presentation helps to get a clearer picture at first glance, the clarity comes at the price of omitting much of the information contained in the BBN. However, one can always go back to the BBN and take a look at the complete distributions.

The question of how to aggregate the assessments of different experts is not solved in a satisfactory way. One problem is that an inter-individual aggregation of expectations involves the question of how to weigh the opinions of different experts. In the present study, an effort has been made to describe the different experts' positions, give overall ranges and discuss the size of deviations, but not to aggregate the individual assessments into measures or indices. It is left to the reader to decide whether she wants to put uniform trust into the assessments of all experts, or give a higher weight to the opinion of single ones.

Finally, the BBN allows for many different scenarios to be run. In the present chapter, a number of them were included and their outcomes were discussed, but many more options are thinkable. It might be of further interest to combine some of the basic scenarios and analyze the effects, e.g., of favorable battery development and subsidies for electric vehicles together on their market chances and the resulting CO_2 emissions for different shares of renewable energies. While this is beyond the scope of the present thesis, for further details, the BBN can be rerun with different parameters.

As the idea of the present approach was to cover the most important determinants of technological development and CO_2 emissions of the German new vehicle fleet, the BBN is rather large in scope. From the many variables which may influence future vehicle fuel and energy consumption, vehicle prices and market shares, only few could be included into the model, their relations have been modeled in a relatively coarse way, and each variable has a small number of possible states. As a scientific tool, this concrete BBN has allowed both to derive useful answers to predefined research questions, and to test and evaluate an innovative approach, while remaining within the boundaries of feasibility.

In the framework of stakeholder dialogues which took part within the BRS research group during the past years, we had the opportunity to present a preliminary version of the present BBN to practitioners working at German financial service providers. It turned out that they found the method to be promising for practical applications, and were interested in building a BBN for their purposes, as well. They argued that, for their needs, it would be an appropriate tool for a more precise in-depth analysis of a more focussed subject area, i.e., they would probably choose a question which relates a a narrower set of variables, and then model their possible states and interdependencies with greater precision than has been done in the present application.

In summary, it has been shown that combining expert assessments with the formal modeling framework of a BBN is a promising approach and that it can be applied for revealing and analyzing expectations on the future development of the German new car fleet under different conditions. BBN are a useful tool for structuring the relationships among important determinants for a given subject area and for quantifying their interdependencies, which permits using them for quantifying the impacts of important drivers, as show in the present application. BBN allow for the inclusion of subjective probabilities and can be used to span a range of reasonably informed assessments provided by different experts. Moreover, BBN offer a valuable mechanism for learning from new information or analyzing hypothetical scenarios. They have been demonstrated to be a valuable tool within an iterative, stakeholder-based science process.

Chapter 5

Conclusion

The present study has been carried out with a twofold aim: On the subject level, examining the development of CO_2 emissions from the German new passenger car fleet in the twenty years to come, and on the method level, testing an innovative combination of expert assessments and Bayesian Belief Networks (BBN). The main ingredients of this work are a series of qualitative expert interviews which have been carried out to gain first insights into available technologies for car GHG emission reduction, a Bayesian Belief Network the structure of which has been derived from the first interview series, and a set of seven individual BBN, specified by eliciting probabilities from a second set of experts. A detailed summary of the qualitative interviews has been given in Section 3.7, and for an in-depth discussion of the BBN approach and its results, see Section 4.6. Here, a short summary is given for both elements of this Ph.D. thesis – first for the subject, and second for the method.

5.1 Subject Level: 2030 Vehicle Technologies and New Car CO_2 Emissions

As a first step of the present investigation, a set of 15 expert interviews was carried out. The aim was to derive a broad picture of car emission reduction options, their potentials and costs up to 2020. The interviews also served to identify key variables and interdependencies for modeling the development of German new car fleet CO_2 emissions.

The experts agreed that in the next years, a bundle of measures will be applied for improving the fuel efficiency of conventional combustion engine cars. In their opinion, such measures can reduce fuel consumption and CO_2 emissions by 10% to nearly 40%. Moreover, hybridization of cars was assessed as relatively likely to proceed, with possible emission reductions from less than 10% up to

45%. Biofuels were expected to play a certain role in the years to come, as well, causing GHG emission changes ranging from an increase in emissions to an emission reduction of 15% for first generation biofuels, and from a more than 50% to a 100% GHG emission reduction for second generation biofuels. Combinations of efficiency measures, hybridization steps and biofuels could be used for decreasing emissions by up to more than 50%. For further options, i.e., lightweight vehicles and plug-in hybrids, expected GHG emission reductions ranged from one third or less to more than half of current emissions. Finally, in regard to technologies such as battery electric vehicles, fuel cells and hydrogen propulsion in general, experts' opinions spanned the full range from nearly no emission reductions to future zero-emission cars.

The less a technology is developed, the more expectations differed among experts, i.e., the larger the ranges of expected emission reductions grew over all experts, and the more experts' probability assessments of technologies to be adopted diverged. Consequently, the emission reduction potential as well as the applicability of technologies that are not yet technically mature is difficult to evaluate reliably, today. Further development of such technologies can initiate learning processes that will help assessing future emission reduction options and costs associated with them in a more cogent way.

In a second step, an expert-based Bayesian Belief Network (BBN) was built in order to quantify the GHG emission reduction potential of technologies where first round experts strongly disagreed, and compare them to expected conventional vehicle emission development. Moreover, the method was exploited for assessing the market chances of different car technologies, and for quantifying the impact of technological and regulatory drivers identified in the first round of interviews. The time frame of the first analysis was extended by ten years to 2030.

The BBN models future characteristics and market chances of three vehicle types, namely internal combustion engine vehicles including mild and full hybrid electric vehicles (ICE), plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV). The general structure of the BBN consists of 46 interconnected variables which specify, among others, battery parameters, the fuel and energy consumption of the different vehicle types, their costs, and their CO_2 emissions in the year 2030. A second round of expert interviews was carried out for quantifying the conditional probabilities for twelve central variables of the BBN. Seven representatives of predominantly German car OEM, mostly high-ranked R&D or environmental experts, were asked to give their assessments, and each of them specified an individual BBN.

To identify possible technology and car emission pathways and their drivers, the networks have been run under different scenarios of future regulation, battery technological development, or fuel and electricity carbon intensity. Some central results regarding 2030 German new car fleet emissions and composition are as follows:

- Under the baseline scenario, the expected values of the different experts' BBN for 2030 German new car fleet CO_2 emissions range from 96 to 128 g/km, well-to-wheel[1]. This is 50 to 65% of the emissions of the 2008 German new fleet.

- None of the single measures that can be implemented within the BBN suffices for a further emission reduction in the view of all experts. But a combination of a higher share of renewables in the electricity mix, a larger share of biofuels in the fuel mix, and a stricter regulation of car CO_2 emissions in the European Union draws the range of 2030 expected new fleet emissions down to 80 to 96 gCO_2/km, which is 40 to 50% of the emissions of the 2008 fleet.

- Technically, in some BBN much lower fleet CO_2 emissions are feasible. When instantiating only the node for 2030 new vehicle fleet emissions, it can be set to minimum values of 30 to 40, 50 to 60, 70 to 80, and 80 to 90 gCO_2/km (twice), respectively, for the five BBN which have been completely specified[2]. This corresponds to expected values of 18 to 44% of the CO_2 emissions of the 2008 German new vehicle fleet. These low emissions are reached, among others, by strongly reducing 2030 ICE fuel consumption to 1.2, 1.8, 2.9, 3.5 and 3.6 l/100km for the different BBN. Reaching such low ICE fuel consumption levels is possible within the BBN specified by the experts, but it is improbable under the scenarios which have been implemented. Thus, it might be fruitful to analyze further measures which could increase the probability of very low 2030 new car fleet emissions, e.g., radical regulation or a turnaround in consumer demand patterns. While this is not possible within the present BBN, they indicate a promising line of extension.

- In the current public debate, BEV are often supposed to be climate-friendly vehicles even at today's electricity mix. The BBN analysis shows that this is not true for the BEV configured by three out of the seven

[1]Well-to-wheel (WTW) emissions relate to the aggregate of emissions over the life cycle of the different types of energy, e.g., for fuel, emissions caused during extraction, transport, processing and burning. All emissions resulting from the BBN are given as WTW figures.

[2]In two BBN, sales share estimates are missing, such that fleet emissions can not be calculated.

experts, which will emit more than 2030 ICE if electricity is as carbon intensive as today. Only with a strong increase of the share of renewable energies all experts agree that 2030 BEV (and PHEV) will be relatively low-emitting vehicles.

- Most experts think that ICE are likely to remain the dominant vehicle type until 2030. Under the baseline scenario, four out of the five experts who have specified market shares assign expected 2030 shares of 80 to 90% to ICE. One expert thinks it is most likely that there will be roughly 50% of ICE and 40% of PHEV. A second expert can imagine a high PHEV share under favorable conditions. For BEV, expected market shares are only a few percentage points except for one expert who accords 15%.

- The previous two points suggest to be cautious about treating electric vehicles as climate neutral, as well as about the German policy goal of having 5 to 6 million electric vehicles on German roads by 2030.

- Experts' 2030 car CO_2 emission estimates coincide best for ICE, where they concentrate on a rather small range, and diverge most for BEV. Possibly, the fact that ICE are a well-known technology has led the estimates of their 2030 emissions to converge, while for BEV, there exists no common picture of what driving profiles they will have to suit and what comfort they will offer. Some experts frame them as city vehicles, while others expect them to be nearly as long-ranged as current ICE.

These results need to be placed in a wider perspective in several regards. First, new vehicle fleet CO_2 emissions per kilometer driven are a valid indicator of the development of emissions from German passenger vehicles only under a 'ceteris paribus' assumption – i.e., as long as the overall fleet size as well as the distance driven per vehicle and the driving profiles (e.g., driving speed, shares of city and overland traveling etc.) remain relatively constant. It also has to be kept in mind that, with an average useful vehicle lifetime of about 12 years, it takes time for the new fleet characteristics to spread to the overall fleet.

Second, in regard to the concern of preventing dangerous anthropogenic climate change, German passenger vehicle CO_2 emissions are but a tiny contributor to a global public good problem. On a global scale, transport made up for 13.1% of anthropogenic GHG emissions in 2004 (Pachauri & Reisinger 2007, Fig. SPM.3, p.5), and Light Duty Vehicles (LDV), in turn, took a share of 43.3% of world vehicle emissions in 2005 (Joint Transport Research Center 2008, Table 1, p.8). Thus, LDV recently contributed roughly 6% of antropogenic GHG emissions. Moreover, from a global perspective, Germany is a small and mature car market, and the strongest car demand currently comes from rapidly industrializing countries like China. The competitive position of the German car industry on the world market raises some hope that, if more efficient car technology can be developed, it may slowly diffuse to the world car fleet. However, in the recent past, industrializing countries' import demand has not exactly focussed on low-emission car technology, but rather on powerful premium cars.

Third, general future trends of mobility patterns and demand are decisive for the role the automotive sector will play in the future and the related emissions. To sketch only two of an infinite set of conceivable futures: A greener future is thinkable, where people reduce the valuation of mobility, move into smaller, rather self-sufficient communities, replace individual traveling by employing communication devices and using public transport, and prefer smaller, more energy efficient cars to large powerful ones. A more energy intensive future is conceivable, as well, where people continue preferring individual mobility, like large, powerful cars both for independence and as status symbols, or buy personal helicopters if they can afford it. Much depends on the development of preferences and social choices, an aspect that has only be touched in a rudimentary fashion within the present approach. Thus, the present results can be seen as one piece in the puzzle of possible development paths in a changing world.

5.2 Method Level: The Expert-based BBN Approach

Apart from providing insights into the development of vehicle technologies and CO_2 emissions until 2030, the present investigation has served the purpose of testing an innovative method. Both BBN and expert elicitation are tools which have been used for wide ranges of applications, but to my knowledge, they have not been combined for revealing expert expectations regarding future events, before.

BBN consist of a graphical model of qualitative dependencies with a probabilistic model superimposed. They exploit Bayes' Rule for learning from new information. Via the learning mechanism, they can be used to identify the impact of changes in some variables on others, as well as to derive the most probable way of achieving a given outcome, which makes them a useful tool for decision support.

The BBN presented in this thesis is strongly based on stakeholder input. In an iterative procedure, expert elicitation has been used both as a basis for setting up the graphical model, and for quantifying the probabilistic model. The fact that BBN allow using different sorts of inputs and dividing the task of network construction into different steps has proven very helpful for this endeavor.

The present approach builds on the concept of subjective probability. The conditional probabilities experts have been asked for reveal their expectations for the future, framed as quantified dependencies. It has been found that it is feasible to elicit the subjective assessments needed to complete the BBN under narrow time constraints, and that experts were able to deal with the concept intuitively. However, some rejected to give distributions because they felt that too few independent variables were explicitly modeled, such that the BBN offered no precise definition of alternative future paths.

For each expert, an individual BBN has been generated. The fully specified BBN allow calculating the probabilities experts assign to different technology pathways and related GHG emissions under a range of future conditions. BBN software implements a learning algorithm based on Bayes' Rule. It allows updating the BBN to learn from new information, a property that was exploited for scenario analysis. Scenario parameters have been treated as new knowledge and the BBN has been run using these values to find out "what if...".

One advantage of the BBN approach is that it is very flexible and user-friendly. While the effects of a number of scenarios have been analyzed within this Ph.D. thesis, numerous other constellations may be of interest for different purposes. It is always possible to return to the BBN, enter different parameter values at little effort, and to process them. However, computational problems draw relatively narrow limits on the size and connectivity of networks. Capacity limits of the software used were reached by processing the present BBN.

The networks specified by the experts contain a lot of information, and different ways of assembling the information from the different experts' BBN outside of the BBN software and displaying it together have been tested in the present report. In order to show in how far experts' opinions coincide or diverge on different questions, the assessments of the different experts have not been aggregated. Aggregation would have implied attaching some sort of weighting scheme to different experts' assessments, and it is intentionally left to the reader to develop her own weighting.

All in all, using expert-based BBN for analyzing a range of future development options has proven a fruitful novel approach, which also allows quantifying the impacts of main drivers. Eliciting the probability tables needed was feasible, and processing this information alongside with scenario parameters led to an abundance of interesting insights. BBN have been shown to be a useful tool in a stakeholder-based, iterative science approach.

Further research should address the balance of network detailedness and feasibility (both regarding elicitation and computational issues), and the handling of outcomes from larger numbers of individually specified BBN. Moreover, it would be an interesting endeavor to iterate the research process once more by feeding back the results from the BBN analysis to the experts and to other stakeholders and recording their reactions. Such an approach could also provide useful insight in how far the formal Bayesian learning meachanism represents the way experts actually adapt their expectations to new knowledge.

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A.1 Qualitative Interview Guideline

Interview-Leitfaden Automobil-Industrie

Überblick über Ablauf und Gliederung des Interviews:
- *Allg. Entwicklung der Automobilbranche in Deutschland*
- *Techniken zur Emissionsreduktion und Einschätzung der Erfolgsaussichten*
- *Bildung von Erwartungen über die Entwicklung in Deutschland*
- *Ausblick*

1. Was denken Sie, wie sich die Automobilbranche in Deutschland in den nächsten Jahren entwickeln wird – was sind Schlagworte zu gravierenden Änderungen?

Nun möchte ich mit Ihnen genauer über das Thema der THG-Emissionen reden.

2. Die Reduktion von Treibhausgas-Emissionen ist ein Thema, das in letzter Zeit in der Autobranche viel diskutiert wird. Wenn man einen Zeitraum von etwa 15 Jahren betrachtet, welchen Einfluss könnte diese Diskussion auf die Entwicklung der Branche haben?

3. Was die Automobilbranche angeht, wird viel darüber gesprochen, dass durch technische Entwicklung die Emissionen gesenkt werden können.
Was meinen Sie, was könnten wichtige Techniken sein, um die Emissionen in den kommenden 15 Jahren zu verringern?

4. Wenn man von der sofortigen Umsetzbarkeit absieht, sehen Sie technische Möglichkeiten, massiv die Emissionen zu senken – im Sinne von technischen Durchbrüchen?
- Halten Sie es für wahrscheinlich, dass solche Durchbrüche stattfinden?
- Was sind mögliche Hindernisse?
- In welchem Zeitrahmen könnte es zu solchen Umbrüchen kommen?

Nun möchte ich mit Ihnen konkreter über die einzelnen Techniken sprechen, insbesondere über ihr Potential, THG-Emissionen zu vermeiden und über ihre Umsetzungschancen.

5. Sie hatten ..., ... und ... genannt. Diese Techniken möchte ich nach und nach durchgehen und ihre Einschätzungen erfragen

5.1 Emissionsreduktionspotenzial:
a) Wieviel Prozent der THG-Emissionen lassen sich mit dieser Technik gegenüber dem Status Quo beim Betrieb des Fahrzeuges einsparen?
b) Wie ändern sich prozentual die Emissionen mit dieser Technik in der Herstellung/Entsorgung der Autos bzw. des Treibstoffes?
c) Was ist der prozentuale Gesamteffekt in einer well-to-wheel Betrachtung?

5.2 Umsetzungsbedingungen:
Was braucht es, um diese Techniken in den kommenden 15 Jahren in D umzusetzen?
Was sind definitiv notwendige Bedingungen für den technischen Wandel?
Was sind die wichtigsten Hindernisse, die aus dem Weg geräumt werden müssten?
Was sind die wichtigsten Anreize, die hinzukommen oder weiterbestehen müssten?

a) wirtschaftlich (Durchsetzbarkeit am Markt)
b) politisch
c) rechtlich
d) kulturell

5.3. Investitionen
In welcher Größenordnung wären Investitionen zur Umsetzung dieser Technik erforderlich?

5.4. Wahrscheinlichkeiten:
Für wie wahrscheinlich halten Sie es, dass sich diese Technik in den kommenden 15 Jahren durchsetzt?
Ranking auf Skala von 1 („wird sich höchstwahrscheinlich nicht durchsetzen“) bis 5 („wird sich höchstwahrscheinlich durchsetzen“)

5. Final:
Erfolgsversprechendste Technik im Sinne der Emissionsreduktion?
(eventuell aus 5.1 ableitbar?)
Erfolgsversprechendste Technik im Sinne der Durchsetzbarkeit?
(eventuell aus 5.4 ableitbar?)

Wir haben jetzt darüber gesprochen, welche Techniken sich künftig durchsetzen könnten. Sehr interessant für unser Forschungsprojekt ist es, zu erfahren, wie solche Einschätzungen gebildet werden.

6. Können Sie etwas dazu sagen, wie solche Einschätzungen (über die zukünftige Entwicklung der Branche) in ihrer Branche gebildet werden? Haben Sie besondere Strategien / Medien / Infoquellen, die dafür genutzt werden können? Welche Rolle spielt dabei die Berufserfahrung?

Jetzt würde ich gerne noch etwas über Ihren Ausblick auf die längerfristige Zukunft der deutschen Automobilbranche erfahren.

7. Langfristiger gesehen, was denken Sie, welche Trends es im Automobilsektor (hinsichtlich Emissionen / Technik) in den kommenden 50 Jahren geben könnte?

8. Haben wir irgendwelche wichtigen Aspekte des Themas Emissionsminderung im Automobilbereich noch nicht angesprochen? Wenn ja, welche?

Vielen Dank.

A.2 BBN Elicitation Protocol

Befragungsbogen

Experteninterview zu den CO2-Emissionen der Deutschen Neuwagenflotte 2030

Befragter:

Datum:

Hintergrund:

- Aufgrund großer Unsicherheiten ist es schwierig, die Entwicklung von Fahrzeugtechnik und CO2 Emissionen bis 2030 einzuschätzen.
- Bayesianische Experten-Netzwerke können genutzt werden, um Zusammenhänge aufzuzeigen und Erwartungen explizit zu machen.
- Die Zusammenhänge im Entwurfs-Netzwerk (Variablen und deren Verknüpfungen) wurden aufbauend auf einer 1. Runde Experten-Interviews bestimmt.
- Vereinfachungen waren nötig, um das Netzwerk handhabbar zu gestalten. Es handelt sich um ein mögliches Netzwerk, nicht um das einzig denkbare.
- In einer zweiten Runde Experten-Interviews sollen einige wesentliche Abhängigkeiten im Netzwerk quantifiziert werden. Gefragt sind die Einschätzungen von Experten, für wie wahrscheinlich sie bestimmte Entwicklungen halten.
- Die interviewten Experten können von den vorgegebenen Zusammenhängen abweichen oder Spannweiten der Variablen-Zustände verändern, wenn dies zu einer besseren Abbildung der Erwartungen beiträgt.
- Ziel der Erhebung: "Was ist, wenn…" Szenarien für 2030 untersuchen; wesentliche Einflüsse herauskristallisieren
- Ein weiteres wesentliches Befragungsergebnis ist die abschliessende Beurteilung des Netzwerkes und der Methode durch die Experten.

1

Zum Bayesianischen Netz (BN):

- Es handelt sich um ein graphisches Modell zur Darstellung von (bedingten) Abhängigkeiten, das mit einem probabilistischen Modell verknüpft wird
- Expertenwissen und Daten können kombiniert werden.
- Lernen aus Daten (sog. Updating, durch Software implementiert) und Fortentwicklung des Netzwerkes sind möglich.

Das Netzwerk unterscheidet zwischen verbrennungsmotorischen Fahrzeugen (ICE), Plug-in Hybriden (PHEV) und batterieelektrischen Fahrzeugen (BEV). Alle Aussagen beziehen sich auf die Neuwagenflotte in Deutschland 2030. Angaben zu folgenden Größen werden erfragt:

A – Benzin- und Energieverbrauch von verbrennungsmotorischen Fahrzeugen (ICE), Plug-in Hybriden (PHEV), und Batteriefahrzeugen (BEV) 2030

B – Batterie-Energie für Plug-In Hybride (PHEV) und Batterieelektrische Fahrzeuge (BEV) 2030

C – Mehrkosten für ICE, PHEV und BEV 2030 gegenüber heutigen ICE

D – Verkaufszahlen für PHEV, BEV und andere Fahrzeuge im Vergleich zu ICE 2030

E – Bewertung des Modells und der Methode

A

Benzin- und Energieverbrauch von verbrennungsmotorischen Fahrzeugen (ICE), Plug-in Hybriden (PHEV), und Batteriefahrzeugen (BEV) 2030

Definition ICE:

Fahrzeuge, die überwiegend von Verbrennungsmotoren angetrieben werden, und sämtliche Energie aus flüssigen oder gasförmigen Kraftstoffen (Benzin, Diesel, Biokraftstoffe, CNG, LPG,…) beziehen. Hybridisierungsschritte sind hier mit einbezogen, soweit keine elektrische Energie aus externen Quellen verwendet wird.

Definition PHEV:

Fahrzeuge, die einerseits einen elektromotorischen Antrieb haben, für den sie Stom aus einer aus externen Stromquellen aufgeladenen Batterie nutzen. Andererseits können sie mithilfe flüssiger oder gasförmiger Kraftstoffe verbrennungsmotorisch fahren. Im vorliegenden Modell fahren sie zu einem Zeitpunkt immer entweder elektrisch, oder verbrennungsmotorisch; nicht gemischt.
Es wird vorausgesetzt, dass PHEV eine elektrische Reichweite von mindestens 30 km haben.

Definition BEV:

Fahrzeuge, die ausschließlich durch elektrische Energie angetrieben werden, die sie aus externen Stromquellen beziehen und an Bord in einer Batterie speichern.

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Einflussgröße:

A-1) EU-CO2-Emissionsgrenze 2020 für verbrennungsmotorische Fahrzeuge (ICE):

In der EU wird ein zweiter Schritt der Regulierung des CO2-Ausstoßen von neuzugelassenen Pkw diskutiert, Details sollen bis 2013 festgelegt werden. Für diese Studie wird angenommen, dass folgende **Grenzwerte (fahrzeugseitig)** ab 2020 für ICE-Fahrzeuge möglich sind:

Grenzwert in gCO2/km	l/100km bei heutigem Treibstoffmix
Keiner (130g ab 2012)	5.25
115 TTW (20g auf Biotreibstoff angerechnet)	4.65
95 TTW	3.85
95 WTW	3.25

Strafe bei Überschreitung des Grenzwertes 2030: 100€ pro neu zugelassenem Pkw pro g Überschreitung des Grenzwertes in der Hersteller-ICEflotte

Anmerkungen:

- Tank to wheel (TTW) bezieht sich auf die Emissionen, die bei der Verbrennung des Kraftstoffes entstehen.
- Well to wheel (WTW) bezeichnet die Betrachtung aller Emissionen, die über die Kette der Energiegewinnung, -umwandlung und –nutzung entstehen.

Expertenbefragung:

A-2) Durchschnittlicher Treibstoffverbrauch neuzugelassener ICE in Deutschland 2030 [l/100km]

Vorausgesetzt, die in der 1. Spalte genannten Regulierungen werden durchgesetzt - wie schätzen Sie den durchschnittlichen Treibstoffverbrauch von 2030 in Deutschland neu zugelassenen ICE PkW ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Verbrauchs-Szenarien.

Anmerkungen:

- Die Verbrauchsangabe bezieht sich auf eine **durchschnittliche Angabe für alle flüssigen Treibstoffe** (Benzin, Diesel, Biokraftstoffe).
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Durchschn. ICE-Treibstoffverbrauch 2030 [l/100km]

ICE CO2 emission limit 2020	1 to 3.5	3.5 to 4	4 to 5	5 to 8
none or 5 25l 100km				
max 115g km TTW or 4 65l 100km				
max 95g km TTW or 3 85l 100km				
lmax 95g km WTW or 3 25l 100km				

Beispiel:

ICE CO2 emission limit 2020	1 to 3.5	3.5 to 4	4 to 5	5 to 8
none or 5 25l 100km	5	10	30	55
max 115g km TTW or 4 65l 100km				
max 95g km TTW or 3 85l 100km				
lmax 95g km WTW or 3 25l 100km				

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Einflüssgröße:

A-3) EU-CO2-Emissionsgrenze 2020 für Plug-In Hybride (PHEV):

Es wird angenommen, dass sich das EU-Emissionslimit auch auf PHEV beziehen könnte. Dabei gilt die Emissionsgrenze nur für die Fahrt im rein verbrennungsmotorischen Modus. Die Emissionsgrenze ist weniger streng als für ICE, da angenommen wird, das PHEV im elektromotorischen Modus weniger Emissionen verursachen und damit im Durchschnitt weniger emittieren als bei verbrennungsmotorischer Fahrt. Um eine Anwendung dieser Regelung auf PHEV mit sehr geringer elektrischer Reichweite auszuschliessen, gilt sie für **PHEV ab 30 km rein elektrischer Reichweite**. Folgende **Grenzwerte** werden untersucht:

Grenzwert in gCO2/km	l/100km bei heutigem Treibstoffmix
Keiner	
115 TTW	4.65

Strafe bei Überschreitung des Grenzwertes 2030: 100€ pro neu zugelassenem Pkw pro g Überschreitung des Grenzwertes in der Hersteller-PHEVflotte

Einflüssgröße:

A-4) PHEV-Batteriegewicht 2030 [kg]

Es werden drei Szenarien für das Gewicht der in PHEV verbauten Batterien 2030 verwendet:

a) 30 bis 100 kg

b) 100 bis 200 kg

c) 200 bis 420 kg

Expertenbefragung:

A-5) Durchschnittlicher Treibstoffverbrauch neuzugelassener PHEV in Deutschland 2030 im verbennungsmotorischen Modus [l/100km]

Vorausgesetzt, die in der 1. Spalte genannten Batteriegewichte treffen zu und die in der 2. Spalte genannten Regulierungen werden durchgesetzt - wie schätzen Sie den durchschnittlichen Treibstoffverbrauch von 2030 in Deutschland neu zugelassenen PHEV ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Verbrauchs-Szenarien.

Anmerkungen:

- Die Verbrauchsangabe bezieht sich auf eine **durchschnittliche Angabe für alle flüssigen Treibstoffe** (Benzin, Diesel, Biokraftstoffe).
- Verbrennungsmotorischer Modus meint Fahren als ICE **ohne Entnahme von Energie aus der Batterie**.
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Durchschn. PHEV-Treibstoffver-
brauch 2030 [l/100km]

PHEV CO2 emission limit 2020	PHEV battery weight (kg)	3 to 4	4 to 5	5 to 8
none	30 to 100			
none	100 to 200			
none	200 to 420			
max 115g km TTW or 4 65l 100km	30 to 100			
max 115g km TTW or 4 65l 100km	100 to 200			
max 115g km TTW or 4 65l 100km	200 to 420			

Expertenbefragung:

A-6) Durchschnittlicher Verbrauch elektrischer Energie neuzugelassener PHEV in Deutschland 2030 im elektrischen Modus [kWh/100km]

Vorausgesetzt, die in der 1. Spalte genannten Batteriegewichte treffen zu - wie schätzen Sie den durchschnittlichen Energieverbrauch von 2030 in Deutschland neu zugelassenen PHEV ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Verbrauchs-Szenarien.

Anmerkungen:

- Elektrisches Fahren bezieht sich auf Fahrten im "Charge Depleting" Modus, **ohne zusätzlichen verbrennungsmotorischen Antrieb**.
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Durchschn. PHEV-Energieverbrauch 2030
[kWh/100km]

PHEV battery weight (kg)	10 to 15	15 to 25	25 to 40
30 to 100			
100 to 200			
200 to 420			

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Einflüssgröße:

A-7) BEV-Batteriegewicht 2030 [kg]

Es werden drei Szenarien für das Gewicht der in BEV verbauten Batterien 2030 verwendet:
a) 50 bis 200 kg
b) 200 bis 350 kg
c) 350 bis 500 kg

Expertenbefragung:

A-8) Durchschnittlicher Verbrauch elektrischer Energie neuzugelassener BEV in Deutschland 2030 [kWh/100km]

Vorausgesetzt, die in der 1. Spalte genannten Batteriegewichte treffen zu - wie schätzen Sie den durchschnittlichen Energieverbrauch von 2030 in Deutschland neu zugelassenen BEV ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Verbrauchs-Szenarien.

Anmerkungen:

- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Durchschn. BEV-Energieverbrauch 2030
[kWh/100km]

BEV battery weight (kg)	10 to 15	15 to 25	25 to 40
50 to 200			
200 to 350			
350 to 500			

B

Batterie-Energie
für Plug-In Hybride (PHEV) und
Batterieelektrische Fahrzeuge (BEV) 2030

Einflussgröße:

B-1) Batteriepreise 2030 [€2008/kWh]

Es werden zwei Szenarien für Batteriepreise 2030 verwendet:

a) 200 €2008

b) 600 €2008

Begründungen:

a) Eurobat und USABC Entwicklungsziele für Li-ion Batterien (optimistisches Szenario)

b) Concawe-Preisschätzung für 2010 (pessimistisches Szenario)

Einflussgröße:

B-2) Spezifische Energie von Batterien 2030 [kWh/kg]

Es werden zwei Szenarien für die spezifische Energie von Batterien 2030 verwendet:

a) 0.12 kWh/kg ←→ 8.33 kg/kWh

b) 0.2 kWh/kg ←→ 5 kg/kWh

Begründungen:

a) ungefähre Obergrenze der Energiedichte heutiger Li-Ion Batterien

b) USABC langfristiges Entwicklungsziel; heutige Expertenabschätzung des Potenzials von Li-Ion Batterien

Expertenbefragung:

B-3) Batterie-Energie PHEV 2030 [kWh]

Vorausgesetzt, die in der 1. Spalte genannten Batteriepreise und die in der 2. Spalte genannten Energiedichten werden realisiert – wie hoch schätzen Sie die speicherbare Gesamtenergie der 2030 in PHEV verbauten Batterien ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Batteriegewichts-Szenarien.

Anmerkungen:

- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Batterie-Energie PHEV 2030[kWh]

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	6 to 20	20 to 35	35 to 50
200	0.12			
200	0.2			
600	0.12			
600	0.2			

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Expertenbefragung:

B-4) Batterie-Energie BEV 2030 [kWh]

Vorausgesetzt, die in der 1. Spalte genannten Batteriepreise und die in der 2. Spalte genannten Energiedichten werden realisiert – wie hoch schätzen Sie die speicherbare Gesamtenergie der 2030 in BEV verbauten Batterien ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Batteriegewichts-Szenarien.

Anmerkungen:

- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Batterie-Energie BEV 2030 [kWh]

Battery costs 2030 (E/kWh)	Battery energy density (kWh/kg)	10 to 20	20 to 40	40 to 60
200	0.12			
200	0.2			
600	0.12			
600	0.2			

C

Mehrkosten für ICE, PHEV und BEV 2030 gegenüber heutigen ICE

Einflüssgröße:

C-1) ICE-Treibstoffverbräuche

Es werden vier Kategorien verwendet wie in A-2 erhoben.

Expertenbefragung:

C-2) Zusätzliche Kosten eines ICE PkW 2030 gegenüber einem heutigen ICE [€2008]

Vorausgesetzt, der in der 1. Spalte genannte Durchschnittsverbrauch wird erreicht – wie schätzen Sie die durchschnittlichen zusätzlichen Kosten eines ICE Fahrzeugs 2030 gegenüber einem heutigen ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Kosten-Szenarien.

Anmerkungen:

- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Zusatzkosten ICE 2030 gegenüber ICE 2008 [€2008]

ICE av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
1 to 3.5				
3.5 to 4				
4 to 5				
5 to 8				

Einflüssgröße:

C-3) PHEV-Treibstoffverbräuche

Es werden vier Kategorien verwendet wie in A-5 erhoben.

Expertenbefragung:

C-4) Zusätzliche Kosten eines PHEV PkW 2030 gegenüber einem heutigen ICE PkW [€2008]

Vorausgesetzt, der in der 1. Spalte genannte Durchschnittsverbrauch wird erreicht – wie schätzen Sie die durchschnittlichen zusätzlichen Kosten des PHEV Fahrzeugs 2030 gegenüber einem heutigen ICE Fahrzeug ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Kosten-Szenarien.

Anmerkungen:

- Zusätzliche Kosten bitte **ohne Batteriekosten** angeben.
- Alle übrigen Kosten, inklusive der **Zusatzkosten für Elektromotor und elektrischen Antrieb**, bitte einbeziehen.
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Zusatzkosten PHEV 2030 gegenüber ICE 2008 [€2008]

PHEV av. fuel cons. 2030 (l/100km)	-1000 to 0	0 to 1000	1000 to 3000	3000 to 5000
3 to 4				
4 to 5				
5 to 8				

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Expertenbefragung:

C-5) Zusätzliche Kosten eines BEV 2030 gegenüber einem heutigen ICE PkW [€2008]

Wie schätzen Sie die durchschnittlichen zusätzlichen Kosten eines BEV Fahrzeugs 2030 gegenüber einem heutigen ICE Fahrzeug ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Kosten-Szenarien.

Anmerkungen:

- Zusätzliche Kosten bitte **ohne Batteriekosten** angeben.
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Zusatzkosten BEV 2030 gegenüber ICE 2008 [€2008]

-5000 to -3000	-3000 to -1000	-1000 to 0	0 to 1000	1000 to 3000

D

Verkaufszahlen für PHEV, BEV und andere Fahrzeuge im Vergleich zu ICE 2030

Einflüssgröße:

D-1) Annuität der Mehrkosten von PHEV gegenüber ICE 2030 [€2008]

Die Variable hat 4 Zustände:

- -3000 bis 0 €2008
- 0 bis 2000 €2008
- 2000 bis 5000 €2008
- 5000 bis 8000 €2008

Die Wahrscheinlichkeiten dieser Zustände werden im Netzwerk berechnet.

Expertenbefragung:

D-2) Verkaufszahlen für PHEV im Vergleich zu ICE 2030 [Stück/100ICE]

Vorausgesetzt, die in der 1. Spalte genannten jährlichen Mehrkosten eines PHEV gegenüber einem ICE PkW treffen zu - wie schätzen Sie die Anzahl verkaufter PHEV je 100 verkaufter ICE PkW im Jahr 2030 ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Verkaufsanzahl-Szenarien.

Anmerkungen:

- Die **jährlichen Mehrkosten** errechnen sich aus den auf die Nutzungsdauer des Fahrzeugs verteilten, verzinsten Mehrkosten in der Anschaffung und der Differenz der variablen Kosten pro Kilometer auf eine durchschnittliche jährliche Fahrleistung gerechnet.
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Verkaufte PHEV pro 100 ICE 2030[Stück/100ICE]

PHEV annual cost difference to ...	0 to 10	10 to 70	70 to 130	130 to 200
-3000 to 0				
0 to 2000				
2000 to 5000				
5000 to 8000				

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Einflüssgröße:

D-3) Annuität der Mehrkosten von BEV gegenüber ICE 2030 [€2008]

Die Variable hat 3 Zustände:

- -5000 bis 0 €2008
- 0 bis 4000 €2008
- 4000 bis 8000 €2008

Die Wahrscheinlichkeiten dieser Zustände werden im Netzwerk berechnet.

Einflüssgröße:

D-4) Reichweite des BEV Fahrzeugs mit einer vollen Batterieladung [km]

Die Variable hat 2 Zustände:

- 30 bis 200 km
- 200 bis 500 km

Die Wahrscheinlichkeiten dieser Zustände werden im Netzwerk berechnet.

Expertenbefragung:

D-5) Verkaufszahlen für BEV im Vergleich zu ICE 2030 [Stück/100ICE]

Vorausgesetzt, die in der 1. Spalte genannten jährlichen Mehrkosten eines BEV gegenüber einem ICE PkW treffen zu und vorausgesetzt, die in der 2. Spalte genannten Reichweiten von BEV werden realisiert - wie schätzen Sie die Anzahl verkaufter BEV je 100 verkaufter ICE PkW im Jahr 2030 ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Verkaufsanzahl-Szenarien.

Anmerkungen:

- Die **jährlichen Mehrkosten** errechnen sich aus den auf die Nutzungsdauer des Fahrzeugs verteilten, verzinsten Mehrkosten in der Anschaffung und der Differenz der variablen Kosten pro Kilometer auf eine durchschnittliche jährliche Fahrleistung gerechnet.
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Verkaufte BEV pro 100 ICE 2030 [Stück/100ICE]

BEV annual cost difference to I...	BEV range (km)	0 to 5	5 to 10	10 to 30
-5000 to 0	30 to 200			
-5000 to 0	200 to 500			
0 to 4000	30 to 200			
0 to 4000	200 to 500			
4000 to 8000	30 to 200			
4000 to 8000	200 to 500			

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Expertenbefragung:

D-6) Verkaufszahlen für andere Fahrzeuge im Vergleich zu ICE 2030 [Stück/100ICE]

Wie schätzen Sie die Anzahl verkaufter anderer PkW je 100 verkaufter ICE PkW im Jahr 2030 ein? Bitte verteilen Sie (zeilenweise) jeweils die Gesamtwahrscheinlichkeit von 100% auf die Verkaufsanzahl-Szenarien.

Anmerkungen:

- Andere PkW sind eine catch-all Variable für Fahrzeugtypen, die keiner der im Netzwerk modellierten Kategorien angehören. Darunter würden z.B. Fahrzeuge fallen, die von Wasserstoff-Brennstoffzellen angetrieben werden.
- Sie können die Intervalle nach Bedarf verändern.

Wahrscheinlichkeitsverteilung für:
Verkaufte andere PkW pro 100 ICE 2030 [Stück/100ICE]

0 to 5	5 to 10	10 to 30

E

Bewertung des Modells und der Methode

Bitte bewerten Sie auf einer einer 5er-Skala:

1) Wie zutreffend sind die Zusammenhänge zwischen den verschiedenen Einflussfaktoren im Netzwerk abgebildet?

Sehr zutreffend ☐ ☐ ☐ ☐ ☐ Überhaupt nicht zutreffend

2) Wie valide erscheinen Ihnen die quantitativen Ergebnisse des Netzwerkes?

Sehr valide ☐ ☐ ☐ ☐ ☐ Überhaupt nicht valide

3) Wie geeignet ist die Methode des Bayesianischen Netzwerkes zur Untersuchung der Fragestellung, wie sich die CO2 Emissionen der deutschen Neuwagenflotte bis 2030 entwickeln könnten?

Sehr geeignet ☐ ☐ ☐ ☐ ☐ Überhaupt nicht geeignet

Zur Anonymisierung:

Darf ich in der Auswertung der Interviewergebnisse…

- Ihren Namen und Ihre Unternehmenszugehörigkeit nennen?
- Ihnen das soeben spezifizierte Bayesianische Netzwerk namentlich zuordnen?

Vielen Dank für Ihre Teilnahme!

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