Decarbonizing the European Automobile Fleet: Impacts of 1.5 °C-Compliant Climate Policies in Germany and Norway

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Decarbonizing the European Automobile Fleet: Impacts of 1.5 °C-compliant Climate Policies in Germany and Norway

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Abstract

This paper focuses on assessing the impact of different policy measures, in particular different vehicle taxation schemes, on the composition of the fleet of newly registered cars in Norway and Germany. For this purpose, a fleet turnover model was extended by an economic model for predicting tax-induced market penetration of different powertrain technologies. The economic model determines a cost-optimal powertrain portfolio of the newly registered passenger cars based on financial and non-financial aspects. Model evaluation was performed for the case of Norway and Germany by means of reference scenarios that map the current taxation and non-financial preferences, such as range anxiety. The reference scenario in both cases overestimates the role of ZEVs, but is able to reflect the differences in regionalities (driven mainly by the taxation). Considering disutility costs leads to a shift away from ZEVs. Among the considered non-financial preferences, range anxiety has the strongest influence. The optimization framework is a valuable predictor of qualitative statements regarding the impact of tax measures on the fleet composition of newly registered passenger cars.

Keywords: Decarbonization, alternative powertrain technologies, powertrain mix, consumer heterogeneity, non-financial preferences, techno-economic modeling, vehicle taxation

JEL Classification Nos.: R48, H30, O38

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## Nomenclature

### Acronyms and abbreviations

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
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<tr>
<td>A</td>
<td>Average</td>
</tr>
<tr>
<td>AFV</td>
<td>Alternative Fuel Vehicle</td>
</tr>
<tr>
<td>BEV</td>
<td>Battery Electric Vehicle</td>
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<tr>
<td>CAPEX</td>
<td>Capital Expenditures</td>
</tr>
<tr>
<td>CNG</td>
<td>Compressed Natural Gas</td>
</tr>
<tr>
<td>EA</td>
<td>Early Adopter</td>
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<td>EM</td>
<td>Early Majority</td>
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<tr>
<td>EV</td>
<td>Electric Vehicle</td>
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<td>F</td>
<td>Frequent</td>
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<tr>
<td>FCEV</td>
<td>Fuel Cell Electric Vehicle</td>
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<tr>
<td>GHG</td>
<td>Greenhouse Gas</td>
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<tr>
<td>HEV</td>
<td>Hybrid Electric Vehicle</td>
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<tr>
<td>HTS</td>
<td>Household Travel Survey</td>
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<tr>
<td>IAM</td>
<td>Integrated Assessment Model</td>
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<tr>
<td>ICE</td>
<td>Internal Combustion Engine</td>
</tr>
<tr>
<td>IEA</td>
<td>International Energy Agency</td>
</tr>
<tr>
<td>LDV</td>
<td>Light Duty Vehicle</td>
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<tr>
<td>LM</td>
<td>Late Majority</td>
</tr>
<tr>
<td>M</td>
<td>Modest</td>
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<tr>
<td>MNL</td>
<td>Multinominal Logit Equation</td>
</tr>
<tr>
<td>nRegs</td>
<td>Number of Registrations</td>
</tr>
<tr>
<td>OPEX</td>
<td>Operation Expenditures</td>
</tr>
<tr>
<td>PFCEV</td>
<td>Plug-In Fuel Cell Electric Vehicle</td>
</tr>
<tr>
<td>PHEV</td>
<td>Plug-In Hybrid Electric Vehicle</td>
</tr>
<tr>
<td>RU</td>
<td>Rural</td>
</tr>
<tr>
<td>SU</td>
<td>Suburban</td>
</tr>
<tr>
<td>TCO</td>
<td>Total Cost of Ownership</td>
</tr>
<tr>
<td>TTW</td>
<td>Tank-to-Wheel</td>
</tr>
<tr>
<td>VAT</td>
<td>Value Added Tax</td>
</tr>
<tr>
<td>vkm</td>
<td>Vehicle kilometers</td>
</tr>
<tr>
<td>WEU</td>
<td>Western Europe</td>
</tr>
<tr>
<td>WTP</td>
<td>Willingness to Pay</td>
</tr>
<tr>
<td>WTT</td>
<td>Well-to-Tank</td>
</tr>
<tr>
<td>WTW</td>
<td>Well-to-Wheel</td>
</tr>
<tr>
<td>ZEV</td>
<td>Zero-Emission Vehicle</td>
</tr>
</tbody>
</table>

### Latin symbols

- $\text{CAPEX}_{pt}$: Powertrain-specific Capital Expenditures
- $p_{\text{baseline}}$: Baseline Price
- $p_{cc}$: Energy Carrier Price
- $p_{\text{purchase}}$: Purchase Price
- $t$: Target Fleet Emissions
- $\text{tax}_{\text{reg}}$: Registration Tax
- $\text{TCO}_{pt,d}^*$: Distance-related, Powertrain-specific Total Cost of Ownership
- $\text{VAT}_{cs}$: Country-specific Value Added Tax
- $c_{\text{CO}_2}$: CO\(_2\) Penalty Payment
- $d_a$: Annual Distance
- $c_{pt,d}$: Distance-related, Powertrain-specific Energy Consumption
- $f$: Average fleet Emissions
- $\text{Inc}_{cs}$: Country-specific Purchase Incentives
- $\text{OPEX}_{pt,d}$: Distance-related, Powertrain-specific Operational Expenditures
1 Introduction

To achieve emission reductions fast enough and sufficiently to limit global warming to less than 1.5 °C according to the Paris Agreement, the European Commission’s (EC) ‘low carbon economy roadmap’ states a necessary reduction of greenhouse gas (GHG) emissions by at least 80% in 2050 compared to 1990 levels.\(^1\) As a consequence, the ‘2030 climate and energy framework’, adopted in 2014, set a 40% GHG emission reduction objective in 2030 compared to 1990 as one of the key targets.\(^2,3\)

Since transport accounts for almost 30% of the EU’s total CO\(_2\) emissions (of which 72% are attributable to road traffic), the EU member states have set the target to reduce transport emissions by 60% by 2050 compared to 1990 levels.\(^4\)

The decarbonization of the European transport sector is anticipated to be realized by a combination of an increase in the penetration of the current vehicle fleet with technologies that offer the possibility of a low carbon footprint, the uptake of carbon-neutral energy carriers, and policies that increase the efficiency of the European member states’ transport systems (such as shifting to different transport modes as well as avoiding traffic jams). Technologies with a low carbon footprint are anticipated to be battery electric vehicles (BEV), fuel cell electric vehicles (FCEV and the plug-in version PFCEV) and plug-in hybrid electric vehicles (PHEV). According to current legislation BEVs, FCEVs and PFCEVs are referred to as zero emission vehicles (ZEV), since their tailpipe CO\(_2\) emissions are zero.

The decarbonization of road transport via electric or hydrogen-powered vehicles requires that the energy carriers used are carbon-neutral. This can only be achieved in line with the decarbonization of the EU energy sector, e.g. through the increased penetration of renewable energy sources.\(^3\) It is expected that the availability of affordable biomass feedstocks will contribute to the decarbonization of the EU transport sector. However, since limited carbon reduction options based on electrification have been identified for aviation and long-distance road freight transport,\(^5,6\) the contribution of advanced biofuels is particularly important for effectively reducing CO\(_2\) in these sectors and will therefore not be considered in this paper.\(^3\)

The focus of this work is on the decarbonization of road transport by increasing the share of ZEVs in the fleet. Considering that only 3% of newly sold cars in the EU in 2017 were ZEVs, however, it is necessary to explore the market penetration barriers in order to develop counteracting mechanisms.\(^7\)

Costs are the major impediment for the large-scale market penetration of ZEVs. Furthermore, consumer concerns regarding the range of a car, its maintenance costs, reliability and safety, and the availability and density of charging and refueling infrastructure influence the purchase decision.\(^3,8\)

Despite declining battery costs, the penetration rate of BEVs in the European vehicle market is still low. For FCEV, an increase in sales was observed for markets and regions with a sufficient diffusion of infrastructure (e.g. more in the US and Japan and less in the EU member states).\(^3\) Past studies on the topic of policy implementations focusing on vehicle adoption behavior have shown that consumers can be nudged to purchase environmentally-friendly cars, despite their higher purchase costs.\(^9,10\)

The Norwegian road transport fleet is an outstanding example of the commercial success of electric passenger cars. The analysis by Bjørkan et al. (2016) shows that according to BEV owners, the greatest incentive to buy is tax exemption.\(^3\) The extent of tax incentives in Norway is far greater than in any EU country.\(^11\) While fiscal incentives are a form of political intervention aimed at promoting clean energy in transport by increasing the share of ZEVs in the total fleet, electric vehicle (EV) markets that are phasing out the fiscal incentives are experiencing a sharp decline in sales (e.g. in Denmark and to a lesser extent in the Netherlands).\(^3\) At present, sales of ZEVs in the EU are mainly driven by the financial support of the respective member states’ governments.\(^3\)

This work presents an assessment of the efficacy of various policies to reduce GHG emissions of passenger cars. Via a techno-economic analysis, effects of such policies on the market penetration of different powertrain technologies are evaluated for the cases of Germany and Norway. The aim of the study is to create and evaluate a model environment that maps the effects of political measures on the market penetration of different drive technologies. It aims at identifying political measures that are neutral or discriminatory with respect to the drive train in a comparative approach. This is accomplished by combining different established models and approaches available in the literature (that build the setup for a fleet model of the Swiss passenger car fleet) with a cost model that is dedicated to reflect the impact of prices, taxation and non-financial consumer preferences on purchase decisions.
The resulting modeling framework can be adjusted to the respective boundary conditions and taxation options in the considered states (Germany and Norway) to allow for a comparison of markedly different transport policies.

The remainder of this paper is organized as follows: Section 2 reviews and categorizes related work using techno-economic policy assessment models for the automotive sector to identify existing shortcomings and evaluate possible modeling approaches. Section 3 explains the methodology used to model the economic part of the European car sector, particularly focusing on purchasing decisions in order to depict the above-mentioned market entry barriers. Section 4 presents the results, while Section 5 concludes with recommended policy actions and fruitful avenues for future research.

2 Review on Transportation Models

In order to determine the appropriate model type and necessary model requirements for an appropriate representation of the fleet development, it is useful to first discuss the different modeling options and their advantages and disadvantages. Different types of models can be used to account for the role of new technologies in climate policies and to analyze the impact of political measures on the fleet composition and development. We distinguish between integrated assessment models (IAM) and explicit modeling approaches.

2.1 Integrated Assessment Models

IAMs describe quantitatively the key processes in the human and earth system and the interactions of human development and natural environment to gain a better understanding of global environmental problems. The aim is to provide policy-relevant insights into issues of global environmental change by examining the way driving factors induce different impacts, taking into account some of the key feedback and feed-forward mechanisms. Integrated modeling denotes the combination of information from many scientific disciplines to model both the human and the earth systems. The term “assessment” describes the general aim of generating useful information for decision-making. Therefore, IAMs require sufficiently detailed modeling to address the problem, yet simple enough to be applicable in assessments, and without loss of transparency due to the complex relationships involved.\textsuperscript{12,13}

Various types of IAMs cover different specific disciplinary focuses. Differences among existing IAMs need to be set in the context of their history. The two main options are IAMs that evolved from technical progress models of energy systems to cover environmental issues and such that have their roots in economics and are based on the assessment of cost-efficient production allocation. While the economy-based models account for consistency between economic sectors, they mostly depict the economy in the form of material flows, biochemical, physical and ecological processes in a simplified way, and therefore limit their capacity to capture feedback mechanisms of the natural system.\textsuperscript{14}

IAMs with a high level of detail in energy end-use technologies are based on system cost-optimization or utility maximization of the representative agent.\textsuperscript{15} Depending on the scope of sectors covered, IAMs can either be general or partial equilibrium models. General equilibrium models compute their equilibrium over all economic sectors. Partial equilibrium models take into account only part of the economy. In this context, most partial equilibrium models either represent the transport sector alone, or coupled with closely related sectors, e.g. the energy sector, either on a global or on a national scale. The examination of policy measures is therefore done by attaining equilibrium only in that particular, directly affected market. Effects on and from any other market are assumed to have a negligible impact.\textsuperscript{12} Explicit modeling approaches in the transportation sector primarily focus on technology or emission comparisons, or compute CO\textsubscript{2} abatement costs of cars. Costs and prices are not determined by an equilibrium concept but exogenously given.

The models presented below were chosen because they represent state-of-the-art tools that are widely used for the medium- to long-term assessment of costs, potentials and consequences of different policy and technology futures and because they differ in terms of scope, model structure and solution algorithms.\textsuperscript{16}

To contribute to the robustness of the knowledge gained, representatives of all the model types above are contained. The modeling of vehicle and fuel choices is either done by discrete choice (logit)
equations or by algorithms minimizing the total system costs.

The modeling frameworks chosen to be shortly presented and compared in the following regarding their structure, content and used algorithms are the Global Change Assessment Model (GCAM), IMAGE, the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE), the Mobility Model (MoMo), Roadmap, and one explicit modeling approach.

**GCAM, IMAGE and MESSAGE** cover all sectors of the energy system, while MoMo and Roadmap cover the global transportation system only. The modeling approach of Kloess et al. (2011) represents an explicit national modeling approach for the Austrian transportation sector. **GCAM, IMAGE** and **MESSAGE** rely on cross-sectoral, endogenous functions to project future development. MoMo, Roadmap and the model of Kloess et al. are based on expert judgements and detailed, country-specific research and expertise. Because of these differences, these models are highly complementary and in some cases can be used jointly to answer questions that individual models cannot answer in isolation.

In the following, a short overview of the individual models is given, and the model structure and key mechanisms are compared to identify the most important differences between the models. The selected modeling frameworks (global and regional) take into account both financial and non-financial preferences of the buyers towards alternative powertrain technologies in the vehicle purchase decision as well as heterogeneous user groups with regard to mobility behavior etc.

**GCAM** by the Pacific Northwest National Laboratory (PNNL) with modification for the transportation sector by the Institute of Transportation Studies (ITS) of the University of California is a global partial equilibrium model. **GCAM** has technologically detailed representations of the economy, the energy sector, land use and water and is linked to a climate model. It is a dynamic recursive model, i.e. decision-makers are not aware of the future when making a decision today. After solving each period, the model uses the resulting status quo, including the consequences of decisions made in that period (e.g. resource depletion) and then performs the same routine for the next time step. The transportation sector is part of the energy end-use module of **GCAM** and consists of four modes: long-distance passenger air travel, (other) passenger travel, international freight shipping, and (other) freight.

**IMAGE** is a global partial equilibrium model, originally developed to assess the global effect of GHG emissions and now primarily used to explore either the future development without changes in economy, technology and policy to generate a baseline scenario or how to avoid unwanted impacts on the global environment by applying suitable policy measures. **IMAGE** focuses on a detailed representation of biophysical processes and possesses a wide range of environmental indicators. For the representation of the agricultural system, an economic model has been included. A process model describes the energy system, but with less detail on economics and policy instruments compared to other energy models. The **TRAVEL** module, which represents the transport sector of the **IMAGE** modeling framework, consists of four modules: the travel modes module, quantifying travel volumes per region for the different mode shares, the fleet module, describing the competition between the available drivetrain technologies, the vehicle module, accounting for efficiency, costs and speed of the different transportation technologies, and the policy module, containing the policies included in the model.

The **TRAVEL** model (**IMAGE**) has similarity with **GCAM** in terms of overall structure, simulation of competition between different transport technologies and modes, but is (contrary to **GCAM**) directly provided with empirical observations of travel time and income budgets. **MESSAGE** by the International Institute for Applied Systems Analysis (IIASA) is a global, intertemporal optimization model that has a wide range of technological detail available, particularly on the supply side of the energy system. **MESSAGE** is linked to other models to map the effects of changes in the energy system on land use, forestry, macroeconomics, air pollution and climate change. The model’s transportation sector has recently been complemented with a detailed representation of technological aspects. MoMo, developed by the International Energy Agency (IEA), is an independent, technology-rich transportation model that interacts with the IEA’s annual optimization modeling system Energy Technology Perspectives (ETP). MoMo aims at projecting travel indicators, energy consumption, pollutant emissions and greenhouse gases generated for worldwide mobility. In the ETP modeling framework, it serves to generate transport energy demand projections that are then fed into the ETP optimization framework.
achieved using a manually iterative process. MoMo models transport activity, energy consumption and GHG as well as local pollutant emissions. It is based on a descriptive approach, i.e. the user is given the opportunity to create ‘what-if’-scenarios with different types of vehicles, fuels, efficiency improvements etc. to examine the effects of different trends on outputs. This approach allows for the development of any type of scenario, disregarding past trends.\textsuperscript{21} The final energy consumption and emission calculation is based on the decomposition into four main components or factors according to the ASIF methodology: activity, shares of the transport modes, fuel intensity of the respective transport modes and carbon intensity of the energy carriers used.\textsuperscript{17,22} The model does not include detailed travel behavior, but considers some basic indicators (such as vehicle ownership dependent on income growth) to derive projections.\textsuperscript{21}

The Roadmap model by the International Council on Clean Transportation (ICCT) was developed with the aim of estimating current and future well-to-wheel (WTW) emissions and energy consumption of the transport sector, assuming different policy scenarios. Since much of the data used for modeling comes from the IEA’s MoMo model, there is structural similarity. The traffic systems of the eleven most important vehicle markets are modeled and aggregated in five regions to enable global analyses for the implementation of new political measures.\textsuperscript{17}

The ALADIN model is an agent-based simulation model for the representation of alternative fuel vehicle sales based on total cost of ownership (TCO) as a decision indicator in Germany. Drawing on large data sets for individual user’s driving behavior, the utility-maximizing driving option is chosen, considering various technological and behavioral restrictions.\textsuperscript{23}

\section{2.2 Explicit Modeling Approaches}

The explicit modeling approach of Kloess et al. (2011) examines the effects of policy measures and technological progress on the Austrian passenger car fleet regarding energy consumption and the related GHG emissions. To account for the impact of prices and income on the fleet development, a technology-rich bottom-up car fleet model is combined with a top-down demand model.\textsuperscript{24} An explicit modeling approach implies that price and income are not calculated endogenously in feedback loops balancing supply and demand with other sectors, but come as a model input. The model consists of four modules, a vehicle technology module, a module for deriving market shares of the available technologies (based on their specific service costs and taking into account different levels of willingness to pay, WTP), a module covering the influences of income, prices and the level of fixed costs on transport demand and, finally, the bottom-up fleet model of the Austrian passenger car fleet. The fleet is thereby modeled in detail in terms of age structure, car characteristics (such as engine power, propulsion technology, curb weight, specific energy consumption and GHG emissions) and user categories. Besides passenger cars, the model contains alternative transport modes (such as public transport).\textsuperscript{24}

The transport sectors of GCAM, MESSAGE, and IMAGE are part of larger, cross-sectoral IAMs. MoMo, Roadmap, and ALADIN are independent models of the transport sector that do not map endogenous feedback from sectors outside the transport system to changes within the transport system (such as the impact of increasing electricity consumption on the price of electricity).\textsuperscript{17} On the other hand, MoMo, Roadmap, and the explicit modeling approach of Kloess et al. have more detailed representations of the transport sector, such as vehicle characteristics, short-term policy objectives and their implementation, and an accurate tracking of vehicle pollutant emissions as a function of vehicle use.\textsuperscript{17,24}

The following subsections compare the ways in which the various models address two fundamental features of transportation policy: (1) how the competition between the available powertrain technologies is modeled; and (2) how policy interventions are depicted. The goal is to provide an insight into the advantages and disadvantages of the respective modeling approaches.

\section{2.3 Modeling Competition Between Different Technologies}

In GCAM the share of each technology and transport mode is estimated based on a nested logit function using the average levelized cost of service of the respective technology or transport mode.\textsuperscript{17,25} The
model solution is based on the set of prices that balances supply and demand in each market in a recursive and iterative process. \(^{17}\) Nested multinomial logit (MNL) models are often used to describe discrete decisions of different actors. Thereby, data-rich environments are particularly suitable for calibration, especially for models that are used to describe decisions in a time period close to the calibration period. In the context of system dynamic (long-term) energy models, MNL equations are used to determine market shares of different technologies based on relative costs or preferences. The advantage of the MNL model type compared to full optimization is the possibility to divide market shares among several technologies (which better match empirical observations).\(^{14}\)

The modeling of competition in IMAGE is cost-based (for both, the vehicle shares within each travel mode as well as between the mode shares themselves) and therefore shows similarities to GCAM: within the ‘cars’ mode, 22 car types compete for market share, determined by a set of MNL-type equations for new investments and a vintage structure for the existing stock, subject to constraints such as the travel-time-budget (TTB), the travel-money-budget (TMB), and a possible emission target. The underlying assumption is that the technologies with the lowest travel costs are used.\(^{14}\)

The MESSAGE model determines the technology selection using a least-cost optimization of the discounted total net cost of each technology, considering limitations on the annual sales growth rate and vehicle fleet turnover.\(^{17, 26}\)

MoMo and Roadmap calculate market shares based on vehicle costs with the underlying assumption that the least-cost option is chosen subject to potential exogenous constraints and inputs.\(^{21, 27}\) The decision algorithm does not account for consumer heterogeneity.

Aladin models competition via utility maximization, whereby utility is given by the combination of TCO, a user-group-dependent WTPM for environmentally friendly technologies, and a cost of limited choice as well as home-charging costs.\(^{28}\)

The explicit modeling approach from Kloess et al. (2011) uses specific service costs as the main decision criterion. Those costs are based on a logit model approach, taking into account heterogeneity in consumer preferences.

The assumed rate of efficiency improvements of the individual technologies is exogenous to all models, whereas the average improvement of energy intensity is endogenous. Table A.A.1 in the Appendix gives a detailed overview of the level of detail used to describe the different transport modes and sectors in the models, as well as the determination of vehicle stock, efficiency and fuel- or energy demand.

### 2.4 Mechanisms for Policy Analysis

The models presented have all been widely used for policy analysis, especially in the areas of energy efficiency standards, carbon policy, monetary policy, and air pollution policy. The detailed mechanisms employed in each model to analyze policies are listed in Table A.1; a brief summary is provided hereafter.

In GCAM, MESSAGE, and IMAGE energy-related variables and travel activity are a cost-dependent output. They are therefore particularly suitable for the analysis of the effects of cost-based policy interventions, such as fuel prices on the fleet composition of road transport and correlated emissions.\(^{13, 17}\)

MoMo and Roadmap are primarily used as backcasting analysis tools (a planning method that starts from a desirable future state and then goes backwards to identify necessary policies and measures to reach that target and connect that defined future scenario to the present) or to analyze possible consequences of regulatory measures. Parameters such as the average efficiency improvement rate, modal share or transport activity are usually exogenously determined by the modelers.\(^{17, 21, 27}\)

In Aladin, policy analysis is either done by specifying an emission target which implies a carbon tax level or through off-line analysis coupled with manually adjusted model inputs (such as purchase price reductions of ZEVs).

The explicit modeling approach by Kloess et al. (2011) also assesses the impact of policy measures via off-line analysis and afterwards manually adjusted model inputs.\(^{24}\)

It is important to note that the role of the different mitigation strategies in achieving a 1.5 °C target according to the Paris Agreement differs among the models: while the economy-based IAMs favor the use of low-carbon fuels as primary mitigation option, followed by efficiency improvements, the transport- and expert-based models support vehicle efficiency improvements, followed by modal shift.\(^{17}\)

After presenting the different models addressing the transport sector and the related economy, and
Table 1: Short overview of model characteristics. (IAM: integrated assessment model, GEM: general equilibrium model, PEM: partial equilibrium model, EXP: explicit modeling approach)

<table>
<thead>
<tr>
<th>Model</th>
<th>Home institution</th>
<th>Regions covered</th>
<th>IAM / PEM / EXP</th>
<th>Vehicle choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>GCAM</td>
<td>JGCRI</td>
<td>Global</td>
<td>IAM, PEM</td>
<td>Based on logit sharing, shares allocated based on average levelized costs of service provision</td>
</tr>
<tr>
<td>MESSAGE</td>
<td>IIASA</td>
<td>Global</td>
<td>IAM, GEM</td>
<td>Least-cost minimisation (full lifecycle) based on discounted net present costs</td>
</tr>
<tr>
<td>IMAGE</td>
<td>PBL</td>
<td>Global</td>
<td>IAM, PEM</td>
<td>Discrete choice (logit) equations based on vehicle passenger-kilometer shares</td>
</tr>
<tr>
<td>MoMo</td>
<td>IEA</td>
<td>Global</td>
<td>EXP</td>
<td>Based on expert judgement, what-if analysis, or backcasting technique</td>
</tr>
<tr>
<td>Roadmap</td>
<td>ICCT</td>
<td>Global</td>
<td>EXP</td>
<td>Based on expert judgement, what-if analysis, or backcasting technique</td>
</tr>
<tr>
<td>Aladin</td>
<td>Fraunhofer ISI</td>
<td>Europe (particular focus on Germany)</td>
<td>EXP</td>
<td>Determination of utility-maximizing driving option, TCO-based</td>
</tr>
<tr>
<td>Explicit</td>
<td>EEG</td>
<td>Austria</td>
<td>EXP</td>
<td>Market shares based on multi-nominal logit model, cost-based</td>
</tr>
<tr>
<td>Our model</td>
<td>ETH</td>
<td>Germany, Norway</td>
<td>EXP</td>
<td>Utility-maximizing driving option, cost-based</td>
</tr>
</tbody>
</table>

the way necessary features can be implemented, the following section summarizes the pros and cons of the different model types.

2.5 Advantages and Disadvantages of the Different Model Types

Since the different model types vary in their strengths and weaknesses, this section serves to identifying the best way to expand our existing fleet model with a market penetration model. In a second step, general research gaps and shortcomings among all types of models are identified. As mentioned above, the main compromise with IAMs is detail versus simplification. Sufficient level of detail is required to include all relevant processes in both the human and earth system. Simplicity is required to ensure sufficient transparency in complex model systems and to explore uncertainties.¹⁴

An important limitation to the level of detail captured in IAMs is the lack of consistent datasets with global coverage. Since models are developed for different purposes, they would differ in terms of scope and detail. In practice, hybrid models such as IAMs are often found, which range between models with a primary focus on the earth system and pure economic models with a focus on the human sphere and time scale.¹⁴ This means that IAMs may not be the perfect option to assess for the detailed impacts of policy measures in the transport sector. In addition, since IAMs represent an economy-wide approach, the model structure excels in trading off efforts in different sectors, i.e. less costly measures in other sectors might be chosen first.²⁹

IAMs are either simulation- or optimization-based. Simulation-based IAMs mostly use MNL-type equations to describe the discrete choices of the different actors. An advantage of the MNL-type model is that they are able to assign market shares to several technologies (in contrast to full optimization, which for the same situation always chooses the same optimal technology), a situation that is often empirically observed. Nevertheless, the main disadvantage of these models is that they do not strive for the optimum state, but commonly for the most likely one.¹⁴

Optimization-based IAMs do result in the system optimum, but not necessarily represent the most likely version of reality.

Further major shortcomings of optimization-based IAMs are: (1) Most IAMs rely on a single policy
lever for decarbonization: the carbon price (based on emissions trading), applied to all emitting sectors, including road transport. Actual climate policy is characterized by a greater variety of sector-specific political incentives, especially in the transport sector, where the carbon price is commonly not used. Therefore, the assessment of concrete political measures and incentives is usually difficult. It is assumed that decision makers respond to political incentives in a way that the system optimum is reached. However, real-world agent behavior is far from being coordinated in an overall system perspective and often follows non-financial preferences that do not usually feature in IAMs. For a detailed assessment of policy impacts on the transport sector only, an explicit modeling approach was thus found to be best suited for our study.

The following subsection identifies and summarizes the general shortcomings of the models that assess the impacts of political measures on the transport sector so far.

McCollum et al. derived three main shortcomings of existing modeling approaches: (1) many models capture only a single "representative" consumer without considering heterogeneity between individuals; (2) models map vehicle purchase decisions purely as a function of capital, fuel and maintenance costs, with non-financial preferences represented only minimally (or not at all); and (3) global energy-economy models do not consider the impact of cultural or other specificities on vehicle choices (which can be described by the country or region in which the purchase decision has to be made).

Yeh et al. as well derived recommendations for future modeling improvements, among others the modeling of user heterogeneity, characterized by different demographic parameters to improve the understanding of vehicle ownership, travel behavior, and urban vs. rural constellation. Since the consideration of different user groups as well as non-financial preferences was found to be crucial in both studies, we derive them as model requirements to be coped with our modeling approach. The following section therefore explains potential approaches to account for those points.

2.6 Modeling of Non-financial Preferences

Since heterogeneous preferences in purchase decisions were found to be critical determinants to successfully model market penetration, it is necessary to explore how to model the non-financial decision aspects.

Potential non-financial attributes influencing the purchase decision could for example be the number of models available, the perceived risk, comfort, acceleration, and other features specific to alternative fuel vehicles (AFV): vehicle range and refueling station availability. These attributes depict potential additional sources of utility (or disutility) in a consumer's perception. Considering these attributes for vehicle choice is often done by monetizing them as 'intangible costs'. Especially for AFVs these non-financial attributes seem to be relevant, since they are still relatively novel, have limited model availability (even among different brands), suffer from limited range and an incomplete coverage of refueling or recharging stations. According to estimates by McCollum et al., nearly all of the total sum of disutility costs is comprised by five non-financial purchase attributes: (1) range anxiety in terms of limited all-electric driving range; (2) refueling station availability for all non-electric vehicles; (3) risk premium describing the attitude towards novel technologies; (4) model variety regarding the number and diversity of vehicle models and brands that are available on the market; and (5) costs for the electric charger installation.

Based on empirical studies, these disutility costs represent the monetized non-financial preferences that were found to be influential determinants of AFV market penetration. They depend on consumer group and technology, but also vary by region and can decline over time (depending on the implemented scenario boundary conditions). Range anxiety, availability of refueling stations and model diversity/availability dominate among the used non-financial preferences in terms of the absolute monetized value.

Range anxiety describes a consumer's perceived discomfort when depending on the limited range of an all-electric vehicle. This disutility cost sub-component is only relevant for BEVs. McCollum et al. (2018) base these costs on the amount a consumer would be willing to spend on rental cars during a year to cover those days when the vehicles all-electric driving range is insufficient. Disutility costs for range anxiety depend on different factors such as a consumer's settlement, driving intensity, and
Refueling station availability represents a consumer’s perceived inconvenience when assessing the ease of access to refueling stations. It is therefore only relevant for powertrain technologies based on liquid fuels, natural gas or hydrogen. The cost is based on the amount of time a driver would need during a refueling event to reach the next refueling station that supplies the fuel used. The risk premium monetizes the attitude of a consumer towards novel technologies, i.e. the willingness of a consumer to adopt a technology. Since it is a measure of the perceived risk associated with a technology on the part of the consumer, it is relevant for all types of alternative fuel vehicle technologies. The cost proxy depends on the stock of a particular vehicle type within a region, since this stock influences the consumer’s perception of the novelty of the respective technology.

Model variety monetizes a consumer’s disposition to avoid new technologies due to the limited availability of models and is therefore exclusively relevant for AFVs. The proxy used for monetizing is the number of sales of a certain vehicle type within a region at a given point in time. The underlying assumption is that a higher sales number of a technology type leads to a greater model variety and availability.

EV charger costs represent the costs for the charger installation for an electric vehicle, either a Level-II charger at home or at work or the partial costs of a shared Level-III public fast-charger as part of the transport network. Hence, this disutility cost sub-component is only relevant for BEVs and PHEVs. It is assumed to remain constant, disregarding the region or point in time.

The mapping of the above-mentioned heterogeneous behavioral characteristics in purchase decisions requires a subdivision of the average consumer into different consumer groups that are characterized by different preferences, sociodemographic characteristics and vehicle usage. The two-stage methodology used by McCollum et al. to disaggregate consumers and disutility costs along the different dimensions is based on various applications, including a proof-of-concept study using the MESSAGE model presented above. The disaggregation of the homogeneous light-duty vehicle mode is carried out along three dimensions, which represent decisive characteristics for the purchase decision: (1) Settlement pattern: Urban – Suburban – Rural; (2) Attitude toward technology adoption: Early Adopter – Early Majority – Late Majority; (3) Vehicle usage intensity: Modest Driver – Average Driver – Frequent Driver.

This disaggregation results in 3x3x3 possible combinations of consumer characteristics and 27 user groups (Figure 1). In a second step, the disutility costs (representing the above explained non-financial preferences) are added on top of the tangible costs already assumed in the model. However, heterogeneity of consumer preferences does not only depend on non-financial attributes but also vary measurably among geographies and cultures, for both financial and non-financial attributes. McCollum et al. (2018) calculate regional multipliers to adjust the disutility costs from the US to other regions. These multipliers reflect the relationship between the different sub-components of the disutility.

Figure 1: Different user groups for representing consumer heterogeneity, according to McCollum et al.
costs and globally available predictor variables. The computed regional multipliers are then used to adjust three disutility cost sub-components (risk premium, range anxiety, and refueling station availability). Figure A.1 in the Appendix shows the different regions represented by the IMAGE model.\textsuperscript{16,33}

To summarize, this paper focuses on the implementation of the five attributes explained above to account for consumer heterogeneity in terms of non-financial preferences. The detailed calculation is based on the methodology proposed by McCollum et al. (2018).

2.7 Model Requirements for the Developed Model

This paper addresses the effectiveness of various policies for the decarbonization of the car sector in Germany and Norway. The proposed methodology is designed to answer specific research questions regarding technological levers in transport policies aimed to reduce overall CO\textsubscript{2} emissions. To overcome the shortcomings of a simplified transport sector modeling as it is commonly found in global IAMs, the methodological setup chosen for this study ranges between a global and a national transport model, combining a technology-rich, bottom-up fleet model of the passenger car fleet with an explicit approach in the form of a top-down model of the economic part for passenger car purchase decisions based on current vehicle prices. Key improvements on the technological side of this model are the consideration of the detailed interplay between the individual driving behavior and EV charging opportunities on the one hand, and the inclusion of insights regarding the mobility demand from household travel survey data on the other hand. Diffusion of different powertrain technologies is not driven by one representative customer, but by choices of endogenously modeled heterogeneous customers, accounting for bounded rationality in terms of non-financial preferences.

The fleet model to which the economic model will be added follows the setup explained in K"ung et al. (2018).\textsuperscript{35} It contains detailed vehicle specification descriptions, propulsion technologies and user behavior, due to the usage of datasets from different European household travel surveys (HTS).\textsuperscript{35} The fleet is mapped using a representative reference vehicle that is converted to the various powertrain technologies for a transparent technology assessment that is not diluted e.g. by preferences for different vehicle classes.

The aim of this paper is to create and calibrate a model environment that maps the effects of political measures on the market penetration of different drive technologies. Research questions are the identification of political measures that are neutral or discriminatory with respect to the drive train in a comparative approach to contribute to the overarching question: What policy mix is needed for the automotive sector to meet a carbon budget of 1.5 °C?

3 Methodology

3.1 Overview

Fig. 2 shows the framework to develop strategies for deriving emission reduction measures and mapping future fleet development and links between the relevant fields. The framework consists of different modules, which are represented by the blue framed boxes. The output calculated by these modules (represented by the light blue boxes) serves as an input for the optimization model. Potential influences on input values are marked in green, general system inputs are depicted in yellow. This paper focuses on the development and assessment of the cost calculation module and the new car registrations optimizer (red dashed boxes).

The stock & flow module models the fleet turnover in time, i.e. it computes the total number of new car registrations for the country under consideration and is calibrated for the time frame from 2016 to 2050.

For the computed new registrations, mobility demand patterns derived from HTS data are assumed and serve as an input for the powertrain converter module.

This module then transforms the new cars into cars with the same characteristics as the initial ones (such as engine power); one car for every powertrain option is considered.\textsuperscript{35}

In a next step, the energy calculator module uses the generated car versions to determine the distance-specific wheel energy demand and the resulting yearly expected fuel consumption based on the HTS
annual mobility patterns. The information regarding fuel consumption and corresponding tank-to-wheel (TTW) CO₂ emissions are stored for all powertrain versions of each newly registered car. Augmented with well-to-tank (WTW) fuel emissions, they serve as an input for the downstream optimization model.

The charging pattern module uses the daily mobility patterns to verify which powertrain version is able to fulfill the required mobility demand.

The cost calculation module then determines the costs associated with a vehicle version on which the purchase decision is based. Since a vehicle’s fuel economy is partly reflected in the annual mileage, the economics of a vehicle can be described in the form of the TCO*, which consists of both the investment and the operating costs (which in turn depend on the kilometers driven). We use the term TCO* since maintenance and insurance costs are not necessarily powertrain-specific and therefore not considered in this analysis, whereas operation costs are considered only for the first 6.2 years of service (see Section 3.2.1). By combining socio-economic information in terms of the disutility costs (see Section 2.6) with the investment and operating costs of a vehicle, we can estimate for each user which powertrain technology makes sense. In summary, the basis for the purchase decision is the sum of purchase price (CAPEX), operating costs (OPEX) and disutility costs (see Figure 3). The sum of TCO* and disutility costs serves as an input for the optimization model. Overall, the optimization model uses the decision costs, the CO₂ emissions (depending on the scope) and the powertrain feasibility (described by the number of infeasible days to calculate disutility costs from range anxiety).

The optimizer chooses the fleet composition of the new registration cohort that minimizes the total costs from an overall system perspective, i.e. the sum of TCO*, disutility costs and a potential CO₂ penalty payment. The latter depends on the legal CO₂ threshold and the implemented penalty price. Assuming that the CO₂ penalty payments imposed on the OEMs is passed on to customers via an increase in the purchase price if the fleet limit is exceeded (for the fleet of newly registered cars), the selected decision costs form a good basis for determining the most likely market penetration (since they represent the costs consumers would consider when making their purchase decision).

The optimizer then yields the optimal fleet composition of newly registered cars, including the TCO* per chosen car and the corresponding CO₂ fleet emissions. This fleet composition is referred to as cost-optimal hereafter.

The economic part of the model is based on car purchase prices from a market analysis of the German car market. The operational costs are also given for Germany. The following sections give a detailed explanation of the methodology used to calculate TCO* and disutility costs, as well as the mathematical model used for determining the cost-optimal solution. As explained above, consumer preferences may vary among geographies and cultures, regarding both financial and non-financial attributes.

Figure 2: Framework in which the optimization model is embedded. MaaS: mobility as a service, TTW: tank-to-wheel, vkm: vehicle kilometers, nRegs: number of registrations, HTS: household travel survey.
3.2 Preprocessing

The preprocessing generates the necessary input data for the optimization model, itself requiring several inputs from the technological fleet model as well as mobility and cost data (see Figure 3). Preprocessing includes the calculation of CAPEX, OPEX, and disutility costs.

3.2.1 Calculation of the Total Cost of Ownership

The CAPEX are based on vehicle purchase prices from the German vehicle market. To map the purchase decision in the different countries or regions, a baseline price $p_{\text{baseline}}$ is determined, which is derived from the German purchase prices minus the VAT. Assuming that within the two considered countries purchase price differences are primarily due to differences in country-specific taxation, the purchase price for the respective country is determined using the baseline price and adding additional taxes (see eqs. (1) and (2)). The (country-specific) VAT ($\text{VAT}_{\text{cs}}$), registration tax ($\text{tax}_{\text{reg}}$) and purchase incentives ($\text{Inc}_{\text{cs}}$) are taken into account.

\[
p_{\text{baseline}} = p_{\text{purchase}} \cdot \frac{1}{1 + \text{VAT}_{\text{Germany}}} \tag{1}
\]

\[
\text{CAPEX}_{\text{cs}} = p_{\text{baseline}} \cdot (1 + \text{VAT}_{\text{cs}}) + \text{tax}_{\text{reg}} + \text{Inc}_{\text{cs}} \tag{2}
\]

For a more transparent observation of the effects of various fiscal measures, the scope is limited to one standard vehicle per powertrain technology, sized similarly to the VW Golf.\textsuperscript{37} Table 2 shows the used purchase prices for Germany, based on Zapf et al. (2019).\textsuperscript{36}

Table 2: Purchase price differences compared to a conventional gasoline vehicle [€].\textsuperscript{36}

<table>
<thead>
<tr>
<th>Powertrain</th>
<th>Markup</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conv. gasoline</td>
<td>22,339</td>
<td>22,339</td>
</tr>
<tr>
<td>Conv. diesel</td>
<td>2,707</td>
<td>25,046</td>
</tr>
<tr>
<td>Conv. CNG</td>
<td>2,301</td>
<td>24,640</td>
</tr>
<tr>
<td>HEV gasoline</td>
<td>1,688</td>
<td>24,027</td>
</tr>
<tr>
<td>HEV diesel</td>
<td>2,301 + 1,688</td>
<td>26,734</td>
</tr>
<tr>
<td>HEV CNG</td>
<td>2,301 + 1,688</td>
<td>26,328</td>
</tr>
<tr>
<td>BEV 20 kWh</td>
<td>7,710</td>
<td>30,049</td>
</tr>
<tr>
<td>Battery price [€/kWh]</td>
<td>250</td>
<td></td>
</tr>
</tbody>
</table>

The calculation of (distance-specific and powertrain-dependent) OPEX requires the distance-related energy consumption for each vehicle...
The product of distance-related energy, annual distance \(d_a\) and price of the used energy carrier (which already includes the tax on consumption) \(p_{ec}\) determines the annual operating costs of the respective vehicle. Since maintenance and insurance costs are not necessarily powertrain-specific, they are not included in the OPEX. The energy carrier prices used for calculation are country-specific and, therefore, listed separately for each country (see Sections 5 and 6).

According to Thiel et al. (2010), the perceived payback period for advanced diesel versus advanced gasoline vehicles (meaning the actual TCO* used by the consumer to weight the convenience of diesel on gasoline) is 6.2 years. Since almost 50% of the vehicle sales in Europe are diesel vehicles (ACEA, 2008b), they conclude that this payback period is acceptable for European customers to consider investing the higher price when making a purchase decision. We therefore use 6.2 years to calculate the OPEX considered for decision making. This removes the need for a discount factor – i.e. 6.2 years represent the annuity factor that accounts for both the actual lifetime and the personal discount factor.

\[
OPEX_{pt,d} = e_{pt,d} \cdot d_a \cdot p_{ec} \cdot 6.2.
\]

\[
TCO^*_{pt,d} = CAPEX_{pt} + OPEX_{pt,d}
\]

The sum of OPEX and CAPEX equals to TCO*. To calculate the costs that serve as an input for the optimization model, the next subsection explains the methodology used to calculate the disutility costs.

### 3.2.2 Consumer Heterogeneity

As explained in Section 2.6, disutility costs vary among user groups. The methodology used is based on the one developed by McCollum et al. with certain adjustments, and considers 27 user groups, depending on the attitude towards technology, settlement type, and driving intensity, as shown in Figure 1. Disutility costs are then calculated for every powertrain version in every user group. For the cost determination, the user inputs depicted in Table 9 in the Appendix are required. They describe different possible scenario developments in time that lead to different disutility costs. Refueling and recharging infrastructure availability determine disutility costs for refueling station availability, the share of new vehicle sales for the AFVs influences the disutility sub-component describing model availability, and the share of the total vehicle stock of the considered AFVs serves as a basis for the disutility cost sub-component ‘risk premium’. The numbers shown represent the AFV-push scenario according to McCollum et al., but can be varied to depict every possible future development. Table A.2 in the Appendix shows the upper cost limits for several sub-components of the disutility costs. The disutility costs for the five sub-components are calculated separately for each powertrain technology/ version and for each user group. User group shares are based on the ones used in the IMAGE modeling framework. Figure A.4 in the Appendix shows the exemplary distribution over the 27 user groups for Western Europe. The region that is described by the term ‘Western Europe’ can be seen in Figure A.1.

In the following, the exact calculation of each component of the disutility costs is explained. According to McCollum et al., disutility costs for range anxiety are based on the amount of money a consumer would be willing to spend to cover the number of infeasible days. Following the lifetime approach used by Lin et al., we consider range anxiety costs for the aforementioned 6.2 years. Since the charging pattern module explained in Section 3.1 allows to calculate the exact number of days per vehicle on which the battery capacity is not sufficient to cover the daily distance demand, we use this number as a calculation basis. Figure 4 shows the schematic methodology used. An additional model input is provided by a list of annual distances and the number of infeasible days for each vehicle (based on daily mobility demand) for the groups urban (frequent, average, modest) and rural (frequent, average, modest), respectively. The suburban group is sampled from the urban data. Range anxiety costs are then given by multiplying the number of infeasible days with the cost of rental cars (which is assumed to be US-$50 per day) and the exchange ratio in euros per dollar.
Figure 4: Schematic calculation of range anxiety costs. UR: urban, RU: rural, M: modest, A: average, F: frequent, EA: early adopter, EM: early majority, LM: late majority

is therefore only relevant for powertrain technologies based on liquid fuels or gas. The cost calculation is a power regression of the form

$$ y = c \cdot x^b $$  \hspace{1cm} (5)$$

where $c$ and $b$ are powertrain-specific constants, while $x$ denotes the inverse of the infrastructure deployment level. A refueling infrastructure availability of 25% means that compared to stations supplying conventional fuels, there are 25% of all stations supplying the fuel considered. Since a consumer’s attitude towards technology does not affect this disutility cost sub-component, there are only nine user-group dependent disutility cost distributions. Since refueling station availability of diesel/gasoline is so ubiquitous at present, costs are assumed to stay constant over time. This is true for both gasoline/diesel ICEs, HEVs and PHEVs. Moreover, since the density of diesel and gasoline station availability is almost the same among all European countries, they are assumed to be equal and are set to zero. The powertrain-specific upper limit of costs due to limited refueling station availability are shown in Table 3, whereas Figure 5 depicts the development of disutility costs due to limited refueling station availability over time for both the US and Western Europe.

Table 3: Maximum disutility costs due to limited refueling station availability in the US.

<table>
<thead>
<tr>
<th>Powertrain technology</th>
<th>Maximum costs [US$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conv. gasoline</td>
<td>0</td>
</tr>
<tr>
<td>Conv. diesel</td>
<td>0</td>
</tr>
<tr>
<td>Conv. CNG</td>
<td>7826</td>
</tr>
<tr>
<td>HEV gasoline</td>
<td>0</td>
</tr>
<tr>
<td>HEV diesel</td>
<td>0</td>
</tr>
<tr>
<td>HEV CNG</td>
<td>7691</td>
</tr>
<tr>
<td>PHEV 12 kWh gasoline</td>
<td>0</td>
</tr>
</tbody>
</table>

The results for Western Europe (WEU) are obtained by determining the costs for the US and a
The subsequent transformation by multiplying the US result with the regional multipliers for WEU.

Figure 5: Exemplary powertrain-specific disutility costs due to refueling station availability, US vs. WEU 2010 - 2050.

Costs representing limited model variety/availability are calculated based on the share of new vehicle sales of the respective powertrain technology (see Table B), given as a model input. Powertrain-specific disutility costs are calculated according to eq. (6), where \( x \) denotes the share of new vehicle sales in percentage points.

\[
y_{pt} = \max \frac{\text{costs}}{8} \cdot \left( (-1833.33) \cdot \ln(80 - (79 \cdot \exp^{-0.013737 \cdot x \cdot 1000}) \cdot \frac{1}{60}) \right) \cdot \frac{1}{1000}
\]  

(6)

The upper limit to model availability costs is shown in Table A.2. Gasoline and diesel vehicles (both ICE and HEV) are assumed to have zero model availability costs in all years. Settlement type, attitude towards technology, and driving intensity do not influence model availability costs, there is one cost distribution only among all user groups. Moreover, they do not vary across regions, i.e. the regional multiplier used to transform disutility costs from the US to Europe is equal to one.

Figure 6: Powertrain-specific disutility costs due to limited model variety, 2010 - 2050.

The magnitude of the risk premium costs is calculated using the share of the total vehicle stock of the considered novel powertrain technology (see Table B). Costs are estimated with a power regression (see eq. (7)), where \( u_{b,tra} \) represents the upper limit to risk premium costs depending on the attitude towards technology of a user group (see Table A.2), \( b \) is the rate with which costs decline and \( x \) describes the share of the total vehicle stock in percentage points. Gasoline and diesel vehicles (both ICE and HEV) are assumed to have zero risk premium costs in all years. Settlement type and driving intensity do not affect risk premium costs. Thus, there are three user groups and cost distributions (see Figure 13).
7), depending solely on a customer’s attitude towards technology. In this case, regional multipliers are applied to the exponential parameters governing the rate of the risk premium decline as the respective vehicle market share grows.33

\[ y_{ta} = u_{ta} \cdot \exp^{b \cdot x \cdot 1000} \]  

(7)

\[ y_{ta} = \begin{cases} 
-2433 \cdot \exp^{(-0.0460888) \cdot x \cdot 1000} & \text{technology attitude: early adopter} \\
725 \cdot \exp^{(-0.0460888) \cdot x \cdot 1000} & \text{technology attitude: early majority} \\
3827 \cdot \exp^{(-0.0460888) \cdot x \cdot 1000} & \text{technology attitude: late majority} 
\end{cases} \]  

(8)

Figure 7: Technology attitude-specific risk premium costs, US vs. WEU 2010 - 2050.

Perceived costs for EV charger installation are assumed to be 1000 US$ per vehicle across all regions and constant over time.33

The decision costs used by the optimizer are then determined from the sum of the TCO* and the five sub-components of disutility costs. Together with the WLTC CO₂ emissions for each powertrain option, optionally the feasibility matrix (specifying whether or not a powertrain version is able to fulfill the daily mobility demand), and the height of the legal CO₂ penalty, they serve as an input for the optimization model explained in the following.

3.3 Optimization Model

The objective of the optimization model is to choose the fleet composition that minimizes the overall perceived costs and, therefore, represents the most likely market penetration. In the following, this problem is simplified to a portfolio optimization problem on a virtual fleet of \( N = 1000 \) vehicles derived from HTS data, which we presume to be representative for the European market. For each vehicle \( i \), we need to choose one powertrain \( j \) among the set of available options \( J \). Doing so incurs the cost \( TCO^{*}_{i,j} \), the perceived costs in the form of the disutility costs, and results in the emissions \( CO_{2,j} \). We assume that we have to carry those costs (e.g. because we have to pre-finance the vehicles) or at least use them for portfolio determination, since we know that a customer’s purchase decision is based on \( TCO^{*} \), disutility costs plus possibly the CO₂ penalty payments \( c_{CO2} \), if the overall CO₂ emissions exceed the policy target. As shown in Figure 8, input parameters of the optimization model are the decision cost matrix \( decision\ cost_{i,j} \) as well as the \( CO_{2,j} \) matrix and optionally a matrix \( y_{i,j} \) relating powertrains to their practicability, while the potential penalty payments are calculated during the optimization.

This results in the following objective function:

\[ \min \left\{ \sum_{i=1}^{1000} \sum_{j \in J} x_{i,j} \cdot (TCO_{i,j} + \text{disutility costs}_{i,j}) + c_{CO2} \right\} \]  

(9)

where

\[ x_{i,j} \in \{0, 1\} \]  

\[ \sum_{j \in J} x_{i,j} = 1 \]  

\[ \sum_{i=1}^{N} x_{i,j} \leq N \]  

\[ TCO^{*}_{i,j} \]  

\[ \text{disutility costs}_{i,j} \]  

\[ c_{CO2} \]  

\[ \text{feasibility matrix} \]  

\[ y_{i,j} \]  

\[ \text{CO}_2 \text{ emissions} \]
• $x_{i,j}$ is a binary decision variable which (if unity) codifies whether powertrain option $j \in J$ is chosen for vehicle $i$. The fact that exactly one powertrain has to be chosen per vehicle is encoded with the constraint

$$
\sum_{j \in J} x_{i,j} = 1 \quad \forall i \in \{1, ..., N\}
$$

(10)

• $c_{CO_2}$ is the CO$_2$ penalty, which is set per default to 95 € per vehicle and g/km that the final fleet exceeds the target:

$$
c_{CO_2} = (f - t) \cdot 95 \cdot \frac{\text{€}}{\text{g/km}} \cdot N
$$

(11)

where $t$ is the target value (which is 95 g/km in the reference case), $N$ is the number of vehicles in the fleet, and $f$ are the average fleet emissions, defined by:

$$
f = \frac{\left(\sum_{i=1}^{N} \sum_{j \in J} x_{i,j} \cdot CO_{2j}\right)}{N}
$$

(12)

• Since eq. (11) does not exclude negative CO$_2$ costs, a maximum constraint is implemented to ensure that the CO$_2$ costs used in the objective function are non-negative:

$$
\text{cost}_{CO_2} = \max(0, c_{CO_2})
$$

(13)

Table 4 summarizes the quantities, parameters and variables used, whereas Figure 8 shows the schematic optimization model. The optimizer yields the cost-optimal fleet composition in terms of the powertrain

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Quantities</strong></td>
<td></td>
</tr>
<tr>
<td>$I = {1, ..., 1000}$</td>
<td>Set of vehicles contained in the HTS fleet</td>
</tr>
<tr>
<td>$J = {\text{Conv., gasol., ...}}$</td>
<td>Set of available powertrains</td>
</tr>
<tr>
<td>$TCO_{i,j}$</td>
<td>Total costs of ownership for vehicle $i$ with powertrain $j$</td>
</tr>
<tr>
<td>$CO_{2j}$</td>
<td>CO$_2$ emissions of a vehicle with powertrain $j$</td>
</tr>
<tr>
<td>$t$</td>
<td>Fleet emissions target value</td>
</tr>
<tr>
<td>$N$</td>
<td>Total amount of vehicles contained in the HTS fleet</td>
</tr>
<tr>
<td><strong>Variables</strong></td>
<td></td>
</tr>
<tr>
<td>$x_{i,j} \in {0, 1}$ $\forall i \in {1, ..., N}, \forall j \in J$</td>
<td>Binary decision variable for powertrain $j$ in vehicle $i$</td>
</tr>
<tr>
<td>$f \in \mathbb{R}_{&gt;0}^{+}$</td>
<td>Average fleet emissions</td>
</tr>
<tr>
<td>$c_{CO_2} \in \mathbb{R}_{&gt;0}^{+}$</td>
<td>Resulting CO$_2$ penalty</td>
</tr>
</tbody>
</table>

chosen for each vehicle, the fleet emissions achieved and the CO$_2$ costs paid (or at least decided to pay since the penalty would be less than choosing more expensive powertrain technologies). To provide a better understanding of the model calibration results, the following section shortly presents the data input and the most interesting characteristics thereof.
3.4 Data Input

Besides the technological and cost parameters that are listed in Appendix G, data inputs used are the annual mileage per vehicle and the number of infeasible days per vehicle and year. The latter is used to calculate range anxiety costs, while the former determines the OPEX.

For model calibration, the current taxation of Norway and Germany is implemented. By checking whether the model results correspond to the current fleet of new registrations, we ensure that the model is able to produce reliable results. Both taxation schemes are therefore shortly explained in the following. Taxes are subdivided into tax on acquisition, tax on ownership, and tax on consumption.

3.4.1 The British National Travel Survey and the Charging Pattern Module

Input on annual mileage as well as the number of infeasible days per year and vehicle are based on the charging pattern module which uses data from the British National Travel Survey (NTS). The NTS includes data regarding the citizens’ weekly mobility and their estimated annual mileage by car. The surveys’ participants are firstly split into six user groups, by their settlement type (urban or rural) and their estimated annual mileage (frequent, average or modest), respectively. In order to supply both required inputs, synthetic annual profiles with daily resolution are then generated. Each profile is obtained by sampling with replacement 53 random weekly schedules from the same user group while retaining the original daily resolution. The last six days are then discarded. The resulting annual profiles have information on the total annual mileage as well as the daily distances driven.

A full account of the detailed distribution of user groups and related characteristics is provided in Figure A.2a in the Appendix.

The second input based on the NTS is the number of infeasible days for given battery sizes (see Figure A.2b in the Appendix). The number of infeasible days (all the days on which the battery capacity is not sufficient to satisfy the mobility demand) decreases with increasing battery capacity. Since the average annual mileage in rural areas is higher than in urban ones, the number of infeasible days is user-group-dependent in a similar way (decreasing with decreasing annual mileage). In consequence, the number of infeasible days is the highest for the user group “rural frequent” and the lowest for the “urban modest” drivers.

3.4.2 Taxation Schemes Implemented

Since Norway is the European country with the largest fleet share of ZEVs (39%), it is especially appropriate for calibration (since it is possible to check whether the optimizer chooses a similar share of ZEVs). Norway has one of the strictest and most environmentally-friendly taxation systems in place, containing a tax on acquisition, a tax on ownership, a tax on consumption, and a tax on usage. Since the tax on usage is locally different, it is not included in the model. Table 5 summarizes the details of the current taxation scheme implemented. Figure A.3a in the Appendix shows the qualitative course of
Table 5: Actual Norwegian taxation.39,40

<table>
<thead>
<tr>
<th>Tax type</th>
<th>Calculation</th>
</tr>
</thead>
</table>
| Tax on acquisition (VAT & registration tax)  | VAT: 0 % for ZEVs and 25 % for others  
Registration tax: based on the sum of tax components related to CO\(_2\) emissions, NO\(_x\) emissions and vehicle weight  
(1) CO\(_2\): taxation amount is subdivided into six bands: for cars emitting between 0 and 39 g CO\(_2\)/km, the tax value is negative with -117 €/g; between 40 and 70 g CO\(_2\)/km, the taxation deduction is -99 €/g; from 71 to 95 g CO\(_2\)/km, the tax equals 97 €/g; maximum rates start above 195 g CO\(_2\)/km with a maximum value of 366 €/g  
(2) NO\(_x\): taxation is given by a linear increasing payment of 7.50 €/(mg/km)  
(3) Vehicle curb weight: taxation amount is subdivided in five classes with rates applying per kilogram: cars with a curb weight of less than (or equal to) 500 kg are excluded from taxation; between 501 and 1,200 kg, taxation is 2.61 €/kg; maximum rates apply for a curb weight greater than 1,500 kg with a tax of 23.68 €/kg; in between, taxation rises linearly  
There are no tax refunds if the sum of all three sub-components is less than zero. |
| Tax on ownership                               | Taxation payment is calculated on a daily basis (i.e. taxes are incurred for each day the vehicle is in use) and depends on the powertrain: gasoline cars, diesel cars with particulate filter, and PHEVs pay 298 € over the course of a year; BEVs and FCEVs are exempted from tax. |
| Tax on consumption (fuel and electricity)     | Gasoline: 0.6609 €/l (including a CO\(_2\) tax of 0.1211 €/l); diesel: 0.5304 €/l (including a CO\(_2\) tax of 0.1389 €/l); the total pump price is 1.665 €/l for gasoline and 1.583 €/l; 65 % of the gasoline pump prices and 58 % of the diesel pump prices are taxes; the price for electricity is on average 0.128 €/kWh with a tax share of 32%.39,40 |

To define a complete scenario, the input factors describing the current state of the art regarding the stock and infrastructure for AFVs in Norway are required (see Table 9 in the Appendix).

The second country used for model calibration is Germany. It is the country with the largest car fleet in Europe as well as the country most data used in this study are based upon. The German taxation differs significantly from the Norwegian one, particularly regarding ZEVs. Table 6 summarizes the taxation currently in place. Contrary to Norway, German VAT applies also to ZEVs. Moreover, there is no registration tax in place that penalizes high-emission vehicles, but only a registration fee of 26 €. Emissions are punished as part of the annual ownership tax, which is a function of the CO\(_2\) emissions per kilometer and the cylinder capacity (see Figure A.3b in the Appendix). Table B depicts the country-specific inputs for the disutility cost calculations. The two country scenarios serve as a data input for the model in the following.

### 4 Results

Comparing the new car registrations resulting from the optimizer with the actual new car registrations for Norway and Germany allows us to evaluate the accuracy of the model. By tweaking input parameters like disutility costs, we analyze the robustness of the model and highlight the most influencing cost components. We expect the resulting fleet composition (determined by the optimization model) to contain a large share of ZEVs for Norway and almost no ZEVs for Germany. Figure 9 shows the composition of the current Norwegian and German fleet of newly registered passenger cars in 2017, divided by powertrain technologies, as well as the average EU28 fleet of newly registered passenger cars. It can be seen that the large share of EVs (BEVs as well as PHEVs) in Norway leads to 37 g CO\(_2\) per kilometer lower fleet emissions than the EU28 average. Conventional diesel and gasoline cars only account for approximately half of the new passenger vehicle registrations, while EVs already had a share of 39% in 2017 and are projected to reach 70% in 2021. In Germany, however, still approximately
Table 6: Actual German taxation.

<table>
<thead>
<tr>
<th>Tax type</th>
<th>Calculation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax on acquisition</td>
<td><strong>VAT</strong>: 19%, powertrain-independent Registration tax: no registration tax, one-time registration fee of €26\textsuperscript{41}</td>
</tr>
<tr>
<td><strong>Tax on ownership</strong></td>
<td>Annual motor vehicle tax depending on CO\textsubscript{2} emissions and cylinder capacity: (1) CO\textsubscript{2}: cars emitting 95 g/km or less are exempt from taxation; above that rate CO\textsubscript{2} emissions are taxed with 2 €/g (2) Cylinder capacity: cylinder capacity based ownership tax increases step-wise, dependent on the energy carrier used; gasoline cars are taxed at a rate of 2 €/100 ccm, diesel cars pay 9.5 €/100 ccm ZEVs are exempt from ownership tax for the first 10 years of service\textsuperscript{39,40}</td>
</tr>
<tr>
<td><strong>Tax on consumption</strong></td>
<td>Gasoline: 0.6609 €/l (including a CO\textsubscript{2} tax of 0.1211 €/l); diesel: 0.5304 €/l (including a CO\textsubscript{2} tax of 0.1389 €/l); the total pump price is 1.665 €/l for gasoline and 1.583 €/l; 65% of the gasoline pump prices and 58% of the diesel pump prices are taxes; the price for electricity is on average 0.128 €/kWh with a tax share of 32%,\textsuperscript{39,40}</td>
</tr>
</tbody>
</table>

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Figure 9: German, Norwegian and EU-28 average powertrain shares of newly registered passenger cars in 2017.\textsuperscript{39}

90\% of the newly registered cars are powered by fossil fuels.\textsuperscript{40}

Figure A.4 in the Appendix shows the user group shares among the Norwegian population. About 80\% of the population lives in cities, 11\% in rural areas, and only 9\% in suburban areas. Shares are almost equally distributed among frequent, average, and modest drivers. Since the attitude of technology of approximately 30\% of the population is described by “early majority” and another 44\% belong to the “late majority”, we expect the negative risk premium to have a minor impact on the results.

### 4.1 The Case of Norway

Since the decision mechanism of the presented optimization model is cost-based, Figures 10a and 10b show the composition of all costs the optimizer takes into account when deciding for one powertrain option. The cost distributions are shown for an exemplary car of the urban user group, frequent driving intensity, and an “early majority” attitude towards technological innovation. OPEX are considered for the first 6.2 years of vehicle usage and therefore make up the relatively smaller part compared to the CAPEX. However, the OPEX shown in the picture cannot be considered as representative but only depict a single car with an annual mileage of 17,620 km. As the distribution of annual mileages varies between 3200 and 28,500 km (see Figure A.2a), they nevertheless represent a reasonable average.

It can be seen that in this case, even the BEV with the largest battery capacity is less expensive than the cheapest car based on fossil fuels. This is due to the fact that ZEVs are excluded from VAT and registration tax in Norway. As the optimization model’s choice of the powertrain portfolio is cost-based, the federal taxes on fossil fuels as well as on the purchase prices of fossil-fuel-based cars favor ZEVs. The fact that they also avoid potential CO\textsubscript{2} penalty payments leads to the conclusion that the only
reason for choosing non-ZEVs would be the impact of non-financial preferences. Possible variations in the disutility costs compared to the chosen version are depicted on the right-hand side of Figures 10a and 10b. Since the depicted cost composition shows the cost composition for one specific vehicle/annual mileage combination, the variations on the right represent the entity of all other possible vehicle/powertrain/annual mileage compositions.

Figure 10: Composition decision costs for the case of Norway. (UR F: urban frequent)

In a next step we therefore explore the impact of the disutility costs, aggregated as well as the respective disutility cost sub-components. Figure 11 depicts the impact of the considered disutility costs on the fleet composition. The reference scenario is represented by the current Norwegian taxation scheme as well as the user input for Norway (used for the disutility cost calculations) as described in Subsection 3.4.2. The left-hand side of the figure shows the current fleet of newly registered cars in 2020. Obviously the model results do not represent reality. The difference between considering and omitting disutility costs is solely given by a wider distribution among the battery sizes of BEVs. In both cases, the entire fleet of newly registered passenger vehicles consists exclusively of BEVs.

Next, to explore the reasons for this discrepancy, we analyze the impact of the disutility cost sub-components on the fleet composition separately. The worst-case cost impact of the attitude towards technology is an additional amount of €3406 per vehicle for the “late majority” group. Regarding the decision cost differences between ZEVs and non-ZEVs (see Figures 10a and 10b), as well as the fact that fossil-fuel-based cars (except for the CNG powertrains) do not suffer from non-financial preferences, the technology attitude is not expected to make a significant difference when applied independently. Range anxiety costs are a linear function of the infeasible days for all user groups. For a BEV with 20 kWh battery capacity they rank between €0 and €8100. Model availability as well as refueling station
availability costs affect mainly the CNG powertrains. While model availability costs do not distinguish between HEV and ICEV CNG, refueling station availability costs are higher for ICEV CNG, since their consumption is higher and, as a consequence, the range lower.

Figure 12a shows the resulting fleet composition when only one of the considered sub-components is implemented. It can be seen that neither refueling station availability nor model availability, risk premium or costs for EV charger installation influence the fleet composition significantly. Range anxiety costs also do not cause a shift to other powertrain technologies, but rather a wider spread along the battery capacities of BEVs. Nevertheless, higher range anxiety costs could lead to a shift towards fossil-fuel-based powertrains if disutility costs compensate the tax offset to conventional cars.

(a) Disutility cost sub-components for the newly registered passenger cars when implementing only one disutility cost component at a time.

(b) Newly registered passenger cars considering different range anxiety costs. (x: factor with which the original costs are multiplied)

Figure 12: Resulting fleet composition for different parameter variations for the case of Norway.

To assess the possibility of necessary changes in the daily range anxiety costs for better representing reality, range anxiety costs are increased step-wise. This is done by increasing the perceived rental price. Figure 12b shows the resulting fleet compositions for increased range anxiety costs. The number in the middle of each of the circular diagrams represents the factor by which these daily costs are increased. An increase of the perceived daily costs for renting a replacement car from €17 to €170, i.e. by a factor of 10 (see Figure 12b), results intuitively in a decrease of BEVs with a smaller battery capacity and a shift towards higher battery capacities. As a general mechanism it can be observed that with
increasing range anxiety costs, the share of BEVs with larger battery capacities increases. The resulting fleet composition compares better with empirical evidence. Beyond range anxiety costs five times higher than the ones assumed originally, the PHEV gasoline starts to be part of the optimal portfolio. However, note that other versions of fossil-fuel-based cars are not chosen.

Figure 10b suggests that this prevalence of BEVs is due to the strong influence of taxes in Norway. As the underlying assumption of our calculations is a standard vehicle, implying that we only look at one single weight/ emission-combination, the registration tax might potentially be overestimated (i.e. by disregarding the potential cost advantages of smaller vehicle classes, since their registration tax might be significantly lower).

The results for Norway suggest a model parameter adaptation in a way that perceived range anxiety costs have to be increased, while the technological parameters that the registration tax is based on have to be adjusted towards smaller vehicle classes. To justify these results, in a next step the model is evaluated for the current German taxation scheme.

4.2 The Case of Germany

The underlying user group shares are identical to those shown in Figure A.4 (since both Germany and Norway are part of the aggregated region ‘Western Europe’ of the IMAGE model). The cost composition is done for the same exemplary vehicle as before, ensuring comparability. As explained in Subsection 3.4.2, the German taxation differs significantly from the Norwegian one: VAT applies to all kinds of powertrains, there is no registration tax in place, and the annual ownership tax (the only tax that penalizes emissions) is far lower than the Norwegian equivalent (the one-time registration tax). BEVs and PHEVs are primarily supported by the one-time registration incentive, which is depicted as a dashed stack. Consequently, purchase costs are lying closer together than in the case of Norway. Figures 13a and 13b show the decision cost composition for all available powertrains. BEVs do no longer represent the (by far) cheapest option, but e.g. the PHEV gasoline might in some cases be even cheaper. Due to the disutility costs related to model- and refueling station availability, CNG drives are still non-competitive in most cases. Furthermore, the gap between the decision costs for BEVs and conventional vehicles is relatively small, so that even slight changes in the disutility costs or OPEX could result in a significantly different portfolio. The impact of non-financial preferences considered is therefore expected to be larger than in the case of Norway. Figures 9 and 14 show the actual composition of the German fleet of newly registered passenger cars for 2017 and 2020. Since 2017, the share of EVs (PHEVs and BEVs) has increased by 7%.

The fleet composition depicted on the left-hand side of Figure 14 is the one that the model results are compared with. The reference scenario is defined by the German taxation and user input as explained in Subsection 3.4.2. The resulting fleet composition in the reference scenario shows a relatively large share of PHEVs together with the BEVs with small battery capacities. The cost-optimal fleet composition without considering disutility costs results in a pure-BEV fleet, as in the case of Norway. However, contrary to the actual fleet composition, conventional cars are not chosen.
Figure 13: Composition decision costs in the case of Germany. (UR F: urban frequent)

Figure 14: Comparison composition of the current German fleet of newly registered passenger cars with the model results, with and without considering disutility costs, and the model results considering solely VAT. 39

As before, we assess the impact of the disutility cost sub-components separately in order to better understand the mechanisms underlying the portfolio distribution. Figure 15a depicts the impact of the respective non-financial preferences on the resulting fleet composition. Considering solely range anxiety costs leads to a shift, away from the BEV with the smallest battery capacity and towards larger battery sizes, PHEVs and HEVs CNG, depending on the annual mileage and the consequently resulting OPEX. Since refueling and model availability costs are not in place in this scenario, the HEV CNG becomes competitive. Refueling station availability costs as stand-alone costs do not show a significant impact
on the powertrain portfolio. Due to the large share of early and late majority consumers, which imply a positive risk premium, the fourth scenario leads to a shift towards PHEVs gasoline as well. Note that the implementation of solely costs for the EV charger installation does not affect the chosen powertrain portfolio.

(a) Disutility cost sub-components for the newly registered passenger cars when implementing only one disutility cost component at a time.

(b) Newly registered passenger cars considering different range anxiety costs.

Figure 15: Resulting fleet composition for different parameter variations for the case of Germany.

Since the presence of range anxiety costs as the only sub-component leads to an increase in fossil-fuel-powered vehicles, Figure 15b explores the impact of increasing its costs. The series is defined by the same setting as in the reference scenario with range anxiety costs increasing while the remaining costs remain constant. Intuitively, increasing range anxiety leads to a larger share of PHEVs, since their range is not limited and in most cases they are cheaper than their conventional equivalent. A further increase of range anxiety costs shifts the remaining BEVs with small battery capacities towards PHEVs gasoline or HEVs diesel or gasoline, depending on the OPEX resulting from the respective annual mileage. Since BEVs with a low number of infeasible days (and consequently a lower annual mileage) switch last, the last steps of increasing range anxiety costs lead to a larger share of HEVs gasoline and diesel (which are both characterized by relatively high fuel costs and, therefore, particularly suitable for vehicles with low mileages).

However, even range anxiety costs ten times higher than the ones initially assumed do not result in a cost-optimal fleet portfolio containing conventional diesel or gasoline cars, as can be observed in reality. The preference of the PHEV powertrain is due to the fact that it is not affected by a limited all-electric range and at the same time less expensive than conventional ICEVs. Figure 13a and 13b suggest a further examination of the impact of purchase incentives and taxes on ownership on the optimized portfolio.

Figure 14 shows the resulting cost-optimal fleet composition considering VAT exclusively (i.e. ignoring purchase incentives as well as taxes on ownership). The fact that almost 60% of the chosen powertrains are conventional gasoline vehicles, while the rest of the fleet consists of HEVs (both diesel and gasoline) confirms the strong impact of incentives and ownership taxes. Compared to the actual newly registered passenger car fleet we observe that the share of conventional gasoline vehicles is predicted accurately, while the share of conventional diesel vehicles that can be observed in reality is substituted by the HEVs share.
5 Discussion and Conclusion

In this paper we extended a bottom-up fleet model featuring detailed technology coverage with an economic model for predicting market penetration of different powertrain technologies based on different taxation schemes in Germany and Norway. The economic model determines a cost-optimal powertrain portfolio of the newly registered passenger cars based on financial as well as non-financial aspects. Decision costs comprise of the purchase prices (adjusted to the respective country), operational expenditures, and five different monetized non-financial preferences disaggregated to 27 user groups.

Model evaluation was performed for the exemplary cases of Norway and Germany, by means of reference scenarios that map the current taxation and non-financial preferences based on regionally dependent proxy variables. Regarding the disutility costs, refueling station availability as well as model variety are primarily related to gas-powered vehicles. Although none of the reference scenarios maps the actual fleet composition of newly registered vehicles, some similar mechanisms were found. The cost-optimal fleet in the reference Norwegian scenario consists almost exclusively of BEVs with small battery capacities, with a 40% share of PHEVs in the case of Germany. In none of the two reference settings conventional powertrains are found to be cost-optimal. The reference scenario therefore in both cases overestimates the role of ZEVs, but is able to reflect the differences in regionalities (reflected mainly by the taxation). The optimizer therefore returns a larger share of fossil-fuel-based vehicles (in this case PHEVs and HEVs) for Germany than for Norway.

Neglecting disutility costs leads to a shift towards ZEVs. Among the considered non-financial preferences, range anxiety has the strongest influence. A more detailed assessment of range anxiety costs shows in both cases that a higher value shifts the powertrain portfolio away from smaller battery sizes of BEVs to an increasing share of PHEVs, which can also be observed empirically. It thus supports the conclusion that increasing range anxiety costs better reflects reality.

Disregarding emission-related taxes (i.e. considering only the VAT for the modeled purchase decisions) favors the choice of conventional powertrains. This could be due to the portfolio limitation of only one reference vehicle per powertrain category. For example, the advantages of smaller conventional vehicles regarding emission- or weight-related taxes are neglected by our streamlined taxation scheme, which makes them less competitive. Taxation in reality (except for the VAT) seems to play a subordinated role for the purchase decisions in both cases. One reason might be the omission of the concept of company cars for which taxation can be deduced. Therefore, the real consumer probably cares less about the tax gap, making the baseline price more decisive.

To summarize, the optimization framework is a valuable predictor of qualitative statements regarding the impact of tax measures on the new registrations, since it is able to reflect the impact of different tax measures despite the mismatch from the current fleet composition. Analyses for both countries suggest that increasing range anxiety costs and lowering the tax load used for optimizing needs to be considered to represent consumer preferences accordingly.

Other possible reasons for the discrepancy between the actual fleet of newly registered passenger cars and the fleet composition returned by the optimization model might be the non-reflection of market dynamics. In both countries, taxation has been the same for several years. However, the fleet composition still changes on a yearly basis, with a steadily increasing share of zero or low emission vehicles. This fact suggests the necessity of modeling reaction time of preferences (financial and non-financial) to federal incentives.

To fully understand the possible impacts of the underlying model assumptions, we discuss them separately in the following. One of the crucial underlying assumptions of the presented modeling framework is the inelastic demand, i.e. changes in mobility demand resulting from price changes are not represented. Regarding the reaction of demand to taxation, it seems appropriate to assume inelastic demand, i.e. with the whole tax/ incentive to be born by the consumer. This is consistent with the exogenous demand model (tied to population). It can also be justified by the increasing competitiveness of the different OEMs in the market of novel powertrains, which reduces their market power, and hence their capacity to "absorb" incentives.

Furthermore, the available portfolio is represented by one reference vehicle per powertrain category. We therefore disregard non-financial preferences in terms of vehicle class. Since for several powertrains not all vehicle classes might be available, this could influence a consumer's decision. Moreover, as
mentioned before, one reference vehicle implies one single taxation per powertrain option. Since taxation in some cases is based on curb weight, as well as on CO$_2$ or NO$_x$ emissions, we might possibly underestimate the market penetration especially of fossil fuel-powered vehicles (since they are exclusively affected by emission taxation so far) due to lower taxation of smaller vehicle classes. Nevertheless, since the emphasis of the presented work was put on the comparison of the advantages or disadvantages of the different powertrain technologies and the correlated non-financial preferences, it seems an appropriate assumption.

We further model purchase prices for the respective countries by adding country-specific taxes to a baseline price. This baseline price has beforehand been calculated by subtracting all taxes that are currently in place (in Germany) from the German purchase price. The German market was chosen as a basis because it provides the most comprehensive vehicle range to compare the price differential of advanced gasoline versus advanced diesel engine cars. This assumption is not fully correct, but given the purpose and the structure of the model, intra-country cost differences are the determining factor rather than the country-specific absolute values. To summarize, the modeling framework presented can be applied to different countries in order to make qualitative statements regarding the fleet composition of newly registered passenger cars when implementing different tax incentives or fines. The underlying technology-rich fleet model as well as the usage of HTS mobility data qualify for the usage of forward looking policy analysis making valid statements. The parameter variations of the respective disutility cost sub-components have shown that results are relatively robust to changes in these input parameters.

Approaches for future research could be the representation of local tax incentives (such as lower or no parking fees, using bus lanes for ZEVs etc.). Besides, a further disaggregation of the regions representing Europe should be considered, especially regarding the distribution of non-financial preference attributes. The implementation of a company car fleet might be a model improvement in terms of better reflecting the impact of taxation on the actual composition of the fleet of newly registered passenger cars.
Appendix

A Country Coverage of the IMAGE Model and Key Characteristics of the Energy-Economy Models

Figure A.1: Regions considered in the IMAGE modeling framework.\textsuperscript{42}
<table>
<thead>
<tr>
<th>Model</th>
<th>Home Institution</th>
<th>Regions Covered</th>
<th>Sectors Covered</th>
<th>Equilibrium Concept and Solution Method</th>
<th>Vehicle Choice Algorithm</th>
<th>Economics of Propulsion Technology as Main Decision Criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>GCAM</td>
<td>IIASA</td>
<td>32 countries/regions</td>
<td>transportation as part of an IAM including all energy sectors, land use, forestry, agriculture, and a climate model</td>
<td>recursive/iterative (simulation), partial-equilibrium model</td>
<td>based on logit sharing, shares allocated based on average levelized costs of service provision;</td>
<td>market share costs, service costs, the service costs of a reference technology, by technology-specific diffusion barriers;</td>
</tr>
<tr>
<td>MESSAGE</td>
<td>MoMo</td>
<td>11 regions</td>
<td>transportation sector only</td>
<td>recursive-dynamic (simulation), partial-equilibrium model</td>
<td>based on expert judgment, what-if analysis, or back-testing technique</td>
<td>market share costs, service costs, the service costs of a reference technology, by technology-specific diffusion barriers;</td>
</tr>
<tr>
<td>IMAGE</td>
<td>Aladin</td>
<td>26 regions/ countries</td>
<td>transportation sector only</td>
<td>'What-if' scenario accounting and simulation model based on the ASIF (activity/structure/intensity/fuel) identity; projections based on the separate IEA ETP models or developed as backcasts</td>
<td>based on expert judgment, what-if analysis, or back-testing technique</td>
<td>market share costs, service costs, the service costs of a reference technology, by technology-specific diffusion barriers;</td>
</tr>
<tr>
<td>MoMo</td>
<td>PBL</td>
<td>13 countries/regions</td>
<td>transportation sector only</td>
<td>optimization model, based on utility maximization</td>
<td>based on expert judgment, what-if analysis, or back-testing technique</td>
<td>market share costs, service costs, the service costs of a reference technology, by technology-specific diffusion barriers;</td>
</tr>
<tr>
<td>Roadmap</td>
<td>ICCT</td>
<td>33 countries/regions</td>
<td>transportation sector only</td>
<td>discrete choice (logit) equations based on vehicle passenger-kilometer shares</td>
<td>based on expert judgment, what-if analysis, or back-testing technique</td>
<td>market share costs, service costs, the service costs of a reference technology, by technology-specific diffusion barriers;</td>
</tr>
<tr>
<td>Aladin</td>
<td>Fraunhofer ISI</td>
<td>16 countries/regions</td>
<td>transportation sector only</td>
<td>'What-if' scenario accounting and simulation model based on the ASIF (activity/structure/intensity/fuel) identity;</td>
<td>based on expert judgment, what-if analysis, or back-testing technique</td>
<td>market share costs, service costs, the service costs of a reference technology, by technology-specific diffusion barriers;</td>
</tr>
<tr>
<td>MoMo Roadmap</td>
<td>EEG</td>
<td>33 countries/regions</td>
<td>transportation sector only</td>
<td>optimization model, based on utility maximization</td>
<td>based on expert judgment, what-if analysis, or back-testing technique</td>
<td>market share costs, service costs, the service costs of a reference technology, by technology-specific diffusion barriers;</td>
</tr>
</tbody>
</table>

Table A.1: Comparison of key characteristics of the energy-economy models considered in this paper.
<table>
<thead>
<tr>
<th>GCAM</th>
<th>MESSAGE</th>
<th>IMAGE</th>
<th>MoMo</th>
<th>Roadmap</th>
<th>Aladin</th>
<th>explicit</th>
</tr>
</thead>
<tbody>
<tr>
<td>light-duty vehicle technology coverage</td>
<td>gasoline/ diesel/ natural-gas ICE, gasoline/ diesel/ natural-gas HEV and PHEV, BEV, FCEV</td>
<td>gasoline/ diesel ICE (low-, medium- and high-efficiency), gasoline/ diesel HEV, natural-gas ICE, natural-gas HEV, biofuel ICE, biofuel HEV, fossil synfuels ICE and HEV, BEV (100 miles range), gasoline/ diesel PHEV (40 miles), FCEV</td>
<td>gasoline/ diesel biofuel ICE, gasoline/ diesel biofuel HEV, BEV, PHEV, FCEV</td>
<td>gasoline/ diesel CNG/ LNG ICE, HEV and PHEV, BEV, FCEV</td>
<td>gasoline/ diesel CNG/ LNG ICE, HEV and PHEV, BEV, FCEV</td>
<td>gasoline/ diesel ICE, PHEV, BEV, REEV</td>
</tr>
<tr>
<td>system boundary of energy and GHG accounting</td>
<td>full fuel cycle of each fuel till delivery to the transportation sector, no other upstream inputs to the sector (e.g. vehicle manufacturing); transportation does not include pipeline energy use/ infrastructural energy used</td>
<td>includes indirect energy use and emissions from fuel production and vehicle manufacture (represented through assumed future energy demands in industrial sector)</td>
<td>direct CO₂ emissions from the passenger transport; possible to account for upstream emissions</td>
<td>tank-to-wheel (TTW) and well-to-tank (WTT) emissions for fuels; indirect land use change for biofuels; excludes lifecycle impacts of vehicle manufacture and end-of-life</td>
<td>TTW emissions, well-to-tank (WTT) emissions for fuels, indirect land use change for biofuels; excludes lifecycle impacts of vehicle manufacture and end-of-life</td>
<td>emissions not observed</td>
</tr>
<tr>
<td>modes of passenger travel</td>
<td>walking, bicycle, bus, rail, car, truck, two-wheelers, three-wheelers, air</td>
<td>LDVs (cars and trucks), bus, rail, two-wheelers, air</td>
<td>foot, bicycle, bus, train, passenger vehicle, high-speed train, and aircraft</td>
<td>LDVs (cars and trucks), bus, rail, two-wheelers, three-wheelers, air</td>
<td>LDVs, buses, passenger rail, two-wheelers, three-wheelers, passenger aircraft</td>
<td>car (private, commercial and company vehicles), HDVs</td>
</tr>
<tr>
<td>passenger travel service demand</td>
<td>demand as a function of demand in the previous time period, GDP ratio, price ratio, and income and price elasticity; price includes the time value of transportation (increasing with wage rate)</td>
<td>estimations based on income (GDP/capita), population, total cost of travel; total passenger transport demand moves toward a saturation point</td>
<td>endogenously determined; function of fuel price, preference factor, income and population</td>
<td>for private vehicles, ownership is a function of income, calibrated to different countries and then to the IEA WEO model</td>
<td>projection based on exogenous changes in GDP, population and fuel prices</td>
<td>real-world driving profiles (mileage, regularity, and distribution of trips for 1 week); simulation for 6000 private cars (HTS-based), 354 commercial cars (own GPS data); extrapolation to whole fleet</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>detailed coverage of the energy supply of the sector including WTW energy and GHG balances of conventional and alternative conversion chains; WTW energy and emission balance of all fuels based on a life cycle analysis (LCA)</td>
</tr>
</tbody>
</table>
passenger transport mode choice endogenous based on total service costs

endogenous based on the average cost of travel (based on cost of technology), subject to constraints on travel time and budget (tendency to faster modes with growing income)

mode split as a function of the travel-time-budget (TTB), and the travel-money-budget (TMB); TTB and TMB criteria are combined with an nested multinomial logit (MNL)-type equation

no mode-share based system

mode-switching as exogenous policy lever

alternative transport modes such as public transport available

within each mode mix of technology selected based on the nested logit functions within each mode mix of technology selected by minimizing costs of fuel and vehicle costs

market shares of technologies determined using MNL-type equations for new investments and a vintage structure for the existing stock, lowest travel-cost technologies are used

technology mix determined using a multi-nominal logit-model (service costs as main decision criterion, diffusion barriers used)

utility maximizing share of each technology is calculated, reduced due to infrastructure and limited vehicle availability

additional technology costs of efficient technologies decline over time

purchase cost of new technology vehicles decline over time (function of time, scale and learning); efficiencies improve as a function of technology uptake, conventional cars become more expensive over time

transport efficiencies specified exogenously

not included costs decline according to technology learning theory; diffusion of electric propulsion systems follows S-shaped curve of technological life cycles

transport cost functions within each mode with each mode's mode share

vehicle costs within each mode with each mode's mode share

exogenous vehicle costs

transport model

technology mix based on expert judgement, what-if analysis, or backcast technique for policy analysis

technology mix based on expert judgement, what-if analysis, or backcast technique for policy analysis

technology cost and efficiency assumptions

purchase cost and efficiency of new technology vehicles decline over time exogenously

additional technology costs of efficient technologies decline over time

purchase cost of new technology vehicles decline over time (function of time, scale and learning); efficiencies improve as a function of technology uptake, conventional cars become more expensive over time

transport efficiencies specified exogenously

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transport cost functions within each mode with each mode's mode share

vehicle costs within each mode with each mode's mode share

exogenous vehicle costs

transport model

technology mix based on expert judgement, what-if analysis, or backcast technique for policy analysis
<table>
<thead>
<tr>
<th>Policy modeling</th>
<th>GCAM</th>
<th>MESSAGE</th>
<th>IMAGE</th>
<th>MoMo</th>
<th>Roadmap</th>
<th>Aladin</th>
<th>explicit</th>
</tr>
</thead>
<tbody>
<tr>
<td>energy efficiency standards</td>
<td>endogenously constrained</td>
<td>exogenously constrained</td>
<td>endogenously constrained</td>
<td>exogenously constrained</td>
<td>exogenously constrained</td>
<td>exogenously constrained</td>
<td>off-line analysis of a policy’s effects serves as model input</td>
</tr>
<tr>
<td>carbon policy</td>
<td>economy- and sector-wide carbon taxes and carbon caps</td>
<td>economy- and sector-wide carbon taxes and carbon caps</td>
<td>endogenous modeling of any policy that affects the net level of energy service demand possible</td>
<td>off-line analysis of the policies effect serves as input into the model</td>
<td>off-line analysis of the policies effect serves as input into the model</td>
<td>possible to specify an emission target; carbon tax is set to a level whereby direct emissions are reduced to this level</td>
<td>off-line analysis of a policy’s effects serves as model input</td>
</tr>
<tr>
<td>monetary policy</td>
<td>endogenous modeling of any policy that affects the net level of energy service demand possible</td>
<td>endogenous modeling of any policy that affects the net level of energy service demand possible</td>
<td>endogenous modeling of any policy that affects the net level of energy service demand possible</td>
<td>modeling of fuel tax policy with fuel cost elasticity; other price policies handled off-line</td>
<td>through off-line analysis</td>
<td>through off-line analysis (implementation e.g. as purchase price reduction, lower taxation of BEVs, special depreciation for company cars)</td>
<td>off-line analysis of a policy’s effects serves as model input</td>
</tr>
<tr>
<td>others</td>
<td>air pollutant standards - exogenous implementation, no economic feedback; endogenously modeling of policies that affect the net level of energy service demand possible</td>
<td>vehicle sales mandates; endogenous modeling of any policy that affects the net level of energy service demand possible</td>
<td>off-line analysis of a policy’s effects serves as model input</td>
<td>off-line analysis of a policy’s effects serves as model input</td>
<td>vehicle conventional pollutant standards, low-sulfur fuels; other policies: off-line analysis of a policy’s effects serves as model input</td>
<td>off-line analysis of a policy’s effects serves as model input</td>
<td>off-line analysis of a policy’s effects serves as model input</td>
</tr>
</tbody>
</table>
B User Input for Disutility Cost Calculations

Table A.2: Upper limit for the various disutility cost sub-components.\(^{33}\)

<table>
<thead>
<tr>
<th>Cost of EV charger installation</th>
<th>1000$/vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 2 @ Home</td>
<td>1.000</td>
</tr>
</tbody>
</table>

* Relevant for the "EV Charger Installation" disutility cost sub-component

Upper limit to model availability cost

| Cost when sales of a particular vehicle type are zero | 8.000         |

* Relevant for the "Model Availability" disutility cost sub-component

Upper limit to risk premium (technology attitude) cost

| Early adopters | -2.433 |
| Early majority | 0.725  |
| Late majority  | 3.827  |

* Relevant for the "Risk Premium" disutility cost sub-component

Table A.3: User input Norway and Germany.\(^{33}\)

<table>
<thead>
<tr>
<th>2020</th>
<th>Norway</th>
<th>Germany</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Refueling and Recharging Infrastructure Availability</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Electric vehicles (EV &amp; PHEV)</td>
<td>80.0%</td>
</tr>
<tr>
<td></td>
<td>H2 vehicles</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Natural gas vehicles</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

* Relevant for the "Refueling Station Availability" disutility cost sub-components

Share of New Vehicle Sales

|      | Electric vehicles (EV & PHEV) | 68.3% | 8.4% |
|      | H2 vehicles | 0.0% | 0.0% |
|      | Natural gas vehicles | 0.0% | 0.3% |

* Relevant for the "Model Availability" disutility cost sub-component

Share of Total Vehicle Stock

|      | Electric vehicles (EV & PHEV) | 14.1% | 0.6% |
|      | H2 vehicles | 0.0% | 0.0% |
|      | Natural gas vehicles | 0.0% | 0.2% |

* Relevant for the "Risk Premium" disutility cost sub-component

C Specificities of the Outputs of the Charging Pattern Module

Figure A.2a shows the distribution of the respective user groups over annual mileage. Intuitively, annual mileage is primarily influenced by the driving intensity and, secondarily, by the settlement type. Thereby annual mileage declines from frequent over average to modest, and from rural to urban.
(a) Distribution of the annual mileages among the user groups.

(b) Number of infeasible days depending on the battery size.

Figure A.2: Statistical evaluation of the characteristics of the outputs of the charging pattern module, based on the British Nation Travel Survey

D  Tax Calculation

(a) Norway

(b) Germany

Figure A.3: Calculation of Taxes for Germany and Norway

E  Consumer Group Shares in Western Europe

Figure A.4: Consumer group shares Germany and Norway
## F Values and Technological Parameters Used for Calculation

### Table A.4: CO₂ Emission Factors for the Energy Carriers / (g/MJ).

<table>
<thead>
<tr>
<th>Energy Carrier</th>
<th>CO₂ Emission Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gasoline</td>
<td>73.8</td>
</tr>
<tr>
<td>Diesel</td>
<td>73.3</td>
</tr>
<tr>
<td>CNG</td>
<td>56.4</td>
</tr>
<tr>
<td>Hydrogen</td>
<td>0</td>
</tr>
<tr>
<td>Electricity</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table A.5: Technological Parameters of Batteries according to the State of the Art.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy Density of battery packs</td>
<td>Wh/m³</td>
<td>620e3</td>
</tr>
<tr>
<td>Energy Density of battery packs</td>
<td>Wh/kg</td>
<td>225</td>
</tr>
<tr>
<td>Battery Sizes</td>
<td>kWh</td>
<td>50, 75, 100</td>
</tr>
</tbody>
</table>

### Table A.6: Powertrain- and distance-specific energy consumption in kWh/km for the worldwide harmonized light duty vehicle test procedure (WLTP) and real driving (RDE)

<table>
<thead>
<tr>
<th>powertrain</th>
<th>mass / (kg)</th>
<th>WLTP electricity</th>
<th>WLTP fuel</th>
<th>RDE electricity</th>
<th>RDE fuel</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEV 20 kWh</td>
<td>1410</td>
<td>0.1254</td>
<td>-</td>
<td>0.1887</td>
<td>-</td>
</tr>
<tr>
<td>BEV 30 kWh</td>
<td>1473</td>
<td>0.1273</td>
<td>-</td>
<td>0.1915</td>
<td>-</td>
</tr>
<tr>
<td>BEV 40 kWh</td>
<td>1537</td>
<td>0.1292</td>
<td>-</td>
<td>0.1943</td>
<td>-</td>
</tr>
<tr>
<td>BEV 50 kWh</td>
<td>1600</td>
<td>0.1311</td>
<td>-</td>
<td>0.1972</td>
<td>-</td>
</tr>
<tr>
<td>BEV 60 kWh</td>
<td>1664</td>
<td>0.1330</td>
<td>-</td>
<td>0.2000</td>
<td>-</td>
</tr>
<tr>
<td>BEV 70 kWh</td>
<td>1727</td>
<td>0.1349</td>
<td>-</td>
<td>0.2029</td>
<td>-</td>
</tr>
<tr>
<td>BEV 80 kWh</td>
<td>1791</td>
<td>0.1368</td>
<td>-</td>
<td>0.2057</td>
<td>-</td>
</tr>
<tr>
<td>BEV 90 kWh</td>
<td>1854</td>
<td>0.1387</td>
<td>-</td>
<td>0.2086</td>
<td>-</td>
</tr>
<tr>
<td>BEV 100 kWh</td>
<td>1918</td>
<td>0.1406</td>
<td>-</td>
<td>0.2114</td>
<td>-</td>
</tr>
<tr>
<td>PHEV-gasol 12 kWh</td>
<td>1419</td>
<td>0.1257</td>
<td>0.3638</td>
<td>0.1891</td>
<td>0.4743</td>
</tr>
<tr>
<td>HEV-gasol</td>
<td>1364</td>
<td>-</td>
<td>0.3545</td>
<td>-</td>
<td>0.4622</td>
</tr>
<tr>
<td>HEV-diesel</td>
<td>1436</td>
<td>-</td>
<td>0.3048</td>
<td>-</td>
<td>0.3982</td>
</tr>
<tr>
<td>HEV-CNG</td>
<td>1444</td>
<td>-</td>
<td>0.3143</td>
<td>-</td>
<td>0.4150</td>
</tr>
<tr>
<td>ICEV-gasol</td>
<td>1360</td>
<td>-</td>
<td>0.4890</td>
<td>-</td>
<td>0.5984</td>
</tr>
<tr>
<td>ICEV-diesel</td>
<td>1455</td>
<td>-</td>
<td>0.4323</td>
<td>-</td>
<td>0.5275</td>
</tr>
<tr>
<td>ICEV-CNG</td>
<td>1440</td>
<td>-</td>
<td>0.5138</td>
<td>-</td>
<td>0.6189</td>
</tr>
</tbody>
</table>
References


6 D. Connolly, B. V. Mathiesen, and I. Ridjan. A comparison between renewable transport fuels that can supplement or replace biofuels in a 100% renewable energy system. Energy, 73:110–125, aug 2014.


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