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# How to integrate real-world user behavior into models of the market diffusion of alternative fuels in passenger cars - An in-depth comparison of three models for Germany

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ABSTRACT

The future market diffusion of alternative fuels in the passenger car sector is of great interest to both carmakers and policymakers in order to decrease $CO_2$ emissions. The decision to buy a car is not totally objective and only partly based on cost. For this reason, those modeling the future market evolution of cars powered by alternative fuels try to include behavioral and non-cost related aspects. This paper analyzes the integration of user behavior into market diffusion models and compares three models that include this aspect. The comparison comprises three parts: first, it compares the modeling approaches, then uses a harmonized data set to model the future market diffusion of alternative fuel vehicles, with and without behavioral aspects. The most important aspects of user behavior included in the models are the use of charging infrastructure, the limited model availability, the consideration of range anxiety as a hampering factor or the willingness-to-pay-more for alternative drivetrains as a supporting factor, as well as a distinction of users' driving distances. User behavior is considered in various ways, but always has a limiting effect on electric vehicle market diffusion. While a model that distinguishes individual users and driving distances stresses the high relevance of this aspect, it is considered less important in models with a more aggregated inclusion of user behavior based on logit functions.

## 1. Introduction

The market diffusion of alternative fuel vehicles (AFVs) is one way to significantly reduce $CO_2$ emissions from the transport sector. Hence, the evolution of AFV markets is important to policymakers, carmakers, and society as a whole. How markets evolve, however, depends heavily on car users and their behavior. Every user reacts differently to prices, costs, the availability of charging infrastructure, driving range and driving comfort. Therefore, this paper focuses on user behavioral aspects in the decision to buy a car, i.e. all aspects in a buying decision that are neither explained by technology nor by cost.

Various previous studies that focus on individual behavior have shown that user preferences have a major influence on the purchase decision of vehicle buyers [1–3]. For example [4], examined the preferences of German car drivers and found that fuel costs had the strongest influence [5], mention users' driving distances as another important aspect, and [6] state that charging infrastructure availability has a large impact. These different preferences make modeling the evolution of the car market challenging and the formulation of car purchase decisions in market models complex, but important. Several literature reviews of market diffusion models for alternative fuel vehicles have revealed that these rarely consider user behavior [7–9]. In their review [8], showed that only six ([5,10–14]) out of twelve papers with a focus on Germany included individual user behavior in the market diffusion model and of these six, three were based on several versions of the same modeling approach ([5,10,14]). In a review of twelve models [15], found that most of them took feedback processes associated with battery cost reductions, word-of-mouth, and charging infrastructure deployment into account, while electric vehicle (EV) model availability, charging time and driving range were given less consideration. As mentioned before, there are numerous factors influencing the adoption of AFVs. For instance Ref. [16], analyzed AFV fleet adoption for firms by identifying the factors affecting the decision. Positive influences for adoption of the

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**Abbreviations:**

| | |
|---|---|
| AFV | Alternative Fuel Vehicles |
| ALADIN | Alternative Automobiles Diffusion and Infrastructure |
| ASTRA | Assessment of Transport Strategies |
| BEV | Battery Electric Vehicle |
| BIO | Bioethanol Vehicle |
| CNG | Compressed Natural Gas |
| DC | Discrete choice |
| FCEV | Fuel Cell Electric Vehicle |
| GHG | Greenhouse Gas |
| HEV | Hybrid Electric Vehicle |
| LPG | Liquefied Petroleum Gas |
| OM | Operations and Maintenance |
| PHEV | Plug-in Hybrid Electric Vehicle |
| TCO | Total Cost of Ownership |
| TE3 | Transport, Energy, Economics, Environment |
| WTPM | Willingness-to-pay-more |

AFVs are linked to economic efficiency, environmental and strategic aspects.

Most of the literature mentioned does not specify how individual user behavior was integrated into the models in detail. This paper performs an analysis with and without user behavior to highlight the differences.

This paper explores how to integrate real-world user behavior when modeling the passenger car market in order to obtain robust results. It focuses specifically on AFV passenger cars in Germany until 2030. The analysis was performed using three different market diffusion models: ALADIN, ASTRA, and TE3, which are all based on simulation methods. Whereas ALADIN is grounded in agent-based modeling, ASTRA and TE3 are based on system dynamics. This paper therefore covers the two main modeling trends in the transport sector – discrete choice (DC) and agent-based models. While agent-based models naturally have a strong focus on users, the focus of DC models varies with the respective goal. As a macro model, ASTRA is better suited to large-scale developments; TE3 has its own module for different user groups.

These three models are representative for the different approaches and enable a detailed examination of the topic. This is not to deny the usefulness of other approaches, but these were beyond the scope of this study and could be explored in future research.

The main objective of this paper is to close the identified research gap by evaluating the impact of integrating user behavior and comparing three different approaches to doing so.

ALADIN (ALternative Automobiles Diffusion and INfrastructure) is an agent-based simulation model of AFV purchasing decisions. Market diffusion is based on individual users' decisions and considers the willingness-to-pay-more (WTPM) for specific drivetrains,[1] brand loyalty, and individual driving data from several thousand vehicles. The system dynamics model ASTRA (ASsessment of TRAnsport Strategies) [17] is an integrated assessment model, which can analyze the impacts of various transport policies and strategies. The car fleet module determines the type and technology of newly purchased cars. The choice depends on vehicle cost variables as well as non-monetary variables such as infrastructure, capacity, and availability, and is based on a logit function (discrete choice). The TE3 model (Transport, Energy, Economics, Environment) [18] – simulates the uptake of powertrain technologies in main car markets. It is based on system dynamics and incorporates time-series econometric regressions. The technology diffusion of the powertrains in TE3 is based on discrete choice frameworks, which consider the behavior of different consumer groups and the evolving attributes of the various car options.

As a first step, the three models were compared regarding their general approach toward aspects that reflect user behavior (Section 2). In a second step, a comparative scenario with similar framework conditions was defined, which can be implemented in each model (scenario 1). A second scenario was then simulated, in which central aspects of user behavior are deactivated (scenario 2). This second scenario makes it possible to identify the effect of considering user behavior on the models' output. The scenario description and results are shown in Section 3. Finally, the differences in the results due to modeling user behavior are outlined in Section 3.4, limitations are discussed, and conclusions drawn for future modeling in Section 4.

## 2. Analysis of modeling approaches

### 2.1. Description of ASTRA

ASTRA is an integrated assessment model that allows an impact analysis of transport policies and strategies. It follows the system dynamics approach and builds on recursive simulations in Vensim®. The original ASTRA was designed for Europe and has been continuously developed for different application purposes and spatial delineations [17]. This paper uses the German ASTRA-M model based on the federal transport forecast 2030 [19] as described in Ref. [20]. The ASTRA model comprises various interconnected modules: a population module, economic module, transport module, vehicle fleet module, infrastructure module, and environmental module. For more details, see Ref. [21].

The vehicle fleet module describes the composition of vehicle fleets for all road traffic modes based on technology-differentiated cohort models. The car fleet model distinguishes seven vehicle sizes (mini, small, compact, middle class, executive, off-road, multi-purpose vehicle) and nine types of drivetrains: gasoline, diesel, compressed natural gas (CNG), liquefied petroleum gas (LPG), hybrid electric vehicles without a power plug (HEV), battery-electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV), bioethanol (BIO) and hydrogen fuel cell electric vehicles (FCEV). The cohort models enable a detailed representation of the age structure and the diffusion of new technologies into the vehicle fleets. The car fleet model consists of (i) new registrations and (ii) cohort-based fleet modeling. It includes vehicle parameters and socio-economic drivers. The demand for new cars depends on the structure of the car fleet, i.e. scrapped and exported cars, the development of population, any further increase in income/GDP, and regional car density. Fig. 1 shows the design of the car fleet model in ASTRA.

The decision to buy a specific type of drivetrain is made by commercial and private drivers following a logit approach with the total cost of ownership (TCO) complemented by non-monetary factors. This results in the degree of diffusion, i.e. market diffusion scenarios for the various technologies. The logit function (discrete choice according to Ref. [22]) for the probability $P$ that a car of drivetrain $i$ within a size class $r$ will be bought at time $t$ is as follows:

$$P(t)_{i,r} = \frac{e^{-\beta_i * U(t)_{i,r} + \varepsilon_i}}{\sum_{i=1}^{n} e^{-\beta_i * U(t)_{i,r} + \varepsilon_i}} \tag{1}$$

Whereby

$$U(t)_{i,r} = \left[TCO(t)_{i,r} + rc(t)_i\right] * \alpha_{i,r} \tag{2}$$

$$TCO(t)_{i,r} = pc(t)_{i,r} + mc(t)_{i,r} + ic(t)_{i,r} + vt(t)_{i,r} + ct(t)_{i,r} + ec(t)_{i,r} \tag{3}$$

and

$$rc(t)_i = \left( cf(t)_i * 2 * dfs(t)_i + tf(t)_i * val(t) \right) * fa(t)_i * \rho_i \tag{4}$$

With $\beta$ = *calibrated logit choice parameter.*
$U$ = *utility function of car type i*r at time t*
$\varepsilon$ = *calibrated logit parameter for share not explained by utility*

[1] In this paper, the terms drivetrain and powertrain are used interchangeably.

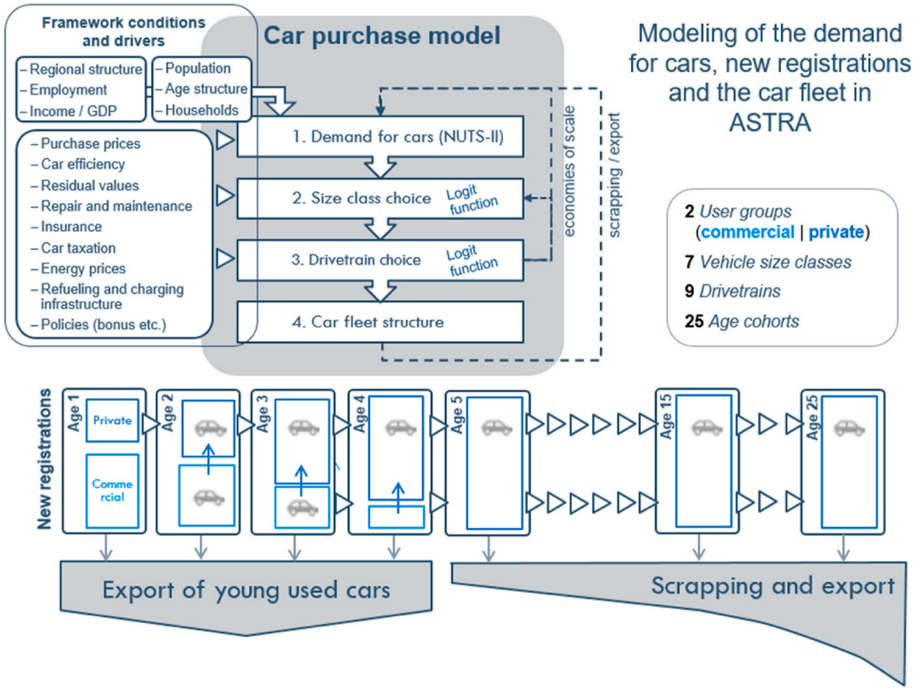


**Fig. 1.** Overview of the car fleet model in ASTRA.

*rc = non-monetary refueling costs [monetarized in €]*
*α = factor for availability of car type i*r (α ≥ 1)*
*cf = costs of refueling action per km [in €/km]*
*dfs = average driving distance to fueling station [in km]*
*tf = time per refueling/recharging actions [in h] (including travel time)*
*val = value of time [in €/h]*
*fa = number of refueling/recharging actions per year*
*ρ = share of public charging of electric drivetrains*

The input data for the $TCO(t)_i$ calculation consists of three blocks: (i) costs of purchasing the vehicle of drivetrain $i$ at time $t$

$$pc(t)_{i,r} = \left[vp(t)_{i,r} - res(t)_{i,r} + VAT\left(vp(t)_{i,r}\right)\right] \Big/ AP \tag{5}$$

With *vp = vehicle purchase price [in €]*.
*res = residual value at the end of amortization period [in €]*
*VAT = VAT for private purchases [in €]*
*AP = amortization period [in years]*

(ii) annual costs (excluding energy costs), namely maintenance and repair $mc(t)_i$, insurance $ic(t)_i$, circulation tax $vt(t)_i$, and the taxation of commercial vehicles $ct(t)_i$ and (iii) energy costs $ec(t)_i$, which depend on the fuel price, and the vehicle's energy consumption and annual mileage.

In addition to monetary costs, non-monetary factors fundamentally drive the choice of a particular car as well. To model the purchase decision, ASTRA-M takes refueling costs $rc(t)_i$ as well as the availability of car models $\alpha$ into account.

Refueling costs are monetarized as follows. The average distance $dfs(t)_i$ is estimated first using the density of refueling stations and the number of locations for public charging. The development of refueling and recharging infrastructure in Germany up to the year 2030 can be found in Ref. [20]. The average distance to the infrastructure together with the average duration of a refueling event or charging process determine one-time refueling costs based on the time and kilometer costs per drivetrain. The frequency of a refueling process differs for each vehicle size and each drivetrain. The range, which results from fuel consumption and tank size or storage capacity together with annual mileage, determines the number of refueling/charging processes $fa(t)_i$ and thus the overall refueling costs per vehicle size and drivetrain.

The availability of car type $i$ is determined by the year of market entry, the share of models offered with certain drive types averaged across all manufacturers, as well as the limited availability of certain vehicle size and drivetrain combinations that would be too expensive.

Other influencing factors that also occur in reality such as brand loyalty, image, design, or perceived safety cannot be monetarized. The effect of these factors is depicted by the parameterization of the logit function.

Finally, the development of the car fleet is determined by new car registrations, the sale of used commercial cars aged one to four years to private owners, the exports of young used cars, and the specific scrapping rates in the various age cohorts. The technology and age differentiation of the car fleet enable the link to the environmental module to determine fuel consumption and emissions, taking the respective mileage from the traffic module into account.

### 2.2. Description of TE3

The TE3 model is a tool that facilitates understanding of the road passenger transport system, with a special focus on car powertrain technologies. TE3 was designed to investigate policy synergies in major electric mobility markets [23] and their impact on energy demand and greenhouse gas (GHG) emissions [18]. TE3 is also based on the system dynamics approach and implemented in Vensim®.

The original version of the model covered China, France, Germany, India, Japan, and the United States, which are linked via battery cost reductions associated with learning from cumulative production. The TE3 model consists of nine modules: population-GDP, car stock, travel demand by car, infrastructure, technology choice, production costs, energy, emissions, and policy. A detailed description of each and information on validation can be found in Ref. [24]. This version of TE3 is available at [25]. This study used an updated version of TE3, in which only Germany is considered and the link to the other markets was de-activated (see Section 3).

The buying decision depends on the anticipated behavior of consumers on the one hand and on the attributes of the different car options on the other hand. This results in the corresponding technology diffusion. Concerning consumer behavior, and in contrast to other models that focus on utility maximization, four consumer segments are represented as connected stock variables in TE3: innovators, habit-oriented consumers, utility maximizers, and low-cost buyers (see Fig. 2). In TE3, no distinction is made between private and commercial users, while two types of car sales are considered: first-time and replacement sales.

Habit-oriented consumers can be understood as the group with repeat car purchases based on the assumption that they retain their current powertrain because they are satisfied with the technology. Following [27], innovators are assumed to be high-income consumers, but they only account for a minor proportion of the car market. Low-cost buyers dominate first-time sales. The underlying assumption is that people are young and have a lower disposable income when making their first car purchase. Hence, the main factor influencing their choice is the purchase price of the car. This attribute also plays a role in the decision of utility maximizers, as can be seen in Fig. 2. The consumer segment of utility maximizers is assumed to have stronger economic rationality and is calculated in the following way:

$$U_{hit} = e^{(\alpha_{it}*pc_{hit})+(\beta_{it}*cost_{hit})+(\gamma_{it}*range_{hit})+(\delta_{it}*time_{hit})+(\varepsilon_{it}*emission_{hit})+(\theta_{it}*coverage_{hit})} \tag{6}$$

With $h =$ *country (in this case Germany)*.
$i =$ *powertrain technology type,*
$t =$ *time,*
$\alpha, \beta, \gamma, \delta, \varepsilon, \theta =$ *utility coefficients*.

The utility maximizers group evaluates six car attributes: *price (pc)*, which refers to the purchase price; *costs*, which are the operating costs including maintenance and fuel costs; *range*, as a value for the driving range; *time*, refers to the charging/refueling time; *emissions,* represents the car's emissions; and *coverage* stands for the charging/refueling station coverage with the corresponding infrastructure. The utility coefficients are based on [24]. A logit probability formulation is used to calculate attractiveness and choice, which can be constrained by powertrain availability and the degree of powertrain popularity. TE3 considers powertrain availability by the year the technology was introduced in the market, but disregards the number of powertrain models available. The stock variable 'degree of popularity' was introduced to reflect changes in powertrain popularity through inflows (gains in popularity) and outflows (losses in popularity).

User behavior in the four consumer segments is captured in a stylized manner in Fig. 2. The attributes of the different powertrain technologies represented in TE3 can be affected by a set of simulated policy measures. For instance, the assumed level of fuel taxes affects the simulated fuel costs and, in turn, the vehicle usage costs. There is no disaggregation of users by driving profile. By default, TE3 assumes a 50% split between electric and non-electric driving for PHEVs. Car attributes such as charging time and range, which can be largely ignored when modeling the decision to purchase a conventional car, become more relevant in the case of electric cars. Thus, the number of car attributes to be considered when evaluating a car option may increase, leading some consumers to behave in a way that is more similar to those showing greater economic rationality over time. This is captured in TE3 by means of a flow variable linking the stock of habit-oriented consumers and the stock of utility maximizers. In this manner, the model caters for the possibility that the weight of each consumer segment in total car demand can change dynamically.

Finally, the evolution of the car stock, disaggregated by age and powertrain, is affected by the inflow (new car sales rate, which in the original version of the model is determined by time-series econometric regressions) and the outflow (scrappage rate, which is influenced by the assumed average car lifetime of 16 years and by the scrappage scheme in Germany in the past).

### 2.3. Description of ALADIN

ALADIN is an agent-based model that simulates the vehicle buying decision of several thousand users based on their preferences and mobility behavior. This buying decision consists of simulating the fit for a BEV and the electric driving share of a PHEV based on a battery simulation that considers driving behavior (STEP 1). The most suitable drivetrain is then determined based on a utility function consisting of the TCO of the drivetrain, the cost of the accompanying individual charging infrastructure, and the WTPM for an electric drivetrain (STEP 2). In a stock model, the share of users with a specific drivetrain is determined annually as the market share of new vehicle registrations, but dampened by the market offer of available vehicles. The vehicle stock is determined (STEP 3) by summing up the market shares with a survival probability. For details, see Fig. 3 and [28].

The second step is described in more detail for comparison. The annuitized utility $U^a_{o,i}(t)$ of user $o$ for drivetrain $i$ is calculated by the TCO of the vehicle $TCO^{a,veh}_{o,i}(t)$, the TCO of individual charging infrastructure $TCO^{a,CI}_{o,i}(t)$ and the WTPM for AFVs $WTPM^a_{o,i}(t)$:

$$U^a_{o,i}(t) = -TCO^{a,veh}_{o,i}(t) - TCO^{a,CI}_{o,i}(t) + WTPM^a_{o,i}(t) \tag{7}$$

Further, the vehicle TCO consists of an annuitized capital expenditure $a^{veh,\ capex}_{o,i}(t)$ and operational expenditure $a^{veh,\ opex}_{o,i}(t)$:

$$TCO^{a,veh}_{o,i}(t) = a^{veh,\ capex}_{o,i}(t) + a^{veh,\ opex}_{o,i}(t) \tag{8}$$

The capital expenditure specific to the individual and the drivetrain is calculated as follows:

$$a^{veh,\ capex}_{o,i}(t) = \left(vp_{r,i}(t)\cdot(1+z(t))^{AP(t)} - res_i(t)\right)\cdot\frac{z(t)}{(1+z(t))^{AP(t)}-1} \tag{9}$$

The vehicle purchase price $vp_{r,i}(t)$ is annuitized with interest rate $z(t)$ and amortization period $AP(t)$, while the residual value after use $res_i(t)$ is subtracted.

The operating expenditure consists of kilometer dependent and independent costs. Use-related costs are calculated based on the individual annual vehicle kilometers traveled $VKT_o$ multiplied by the energy consumption differentiated into electric driving (share of electric driving $(t)$ multiplied by electric consumption $c^e_{r,i}$) and non-electric driving (with conventional consumption $c^c_{r,i}$) plus the operations and maintenance costs $k^{mc}_{r,i}(t)$. The annual vehicle tax $k^{tax}_{r,i}(t)$ is added independently of a user's driving behavior.

$$a^{veh,\ opex}_{o,i}(t) = VKT_i\cdot\left(s_i(t)\cdot c^e_{r,i} + (1-s_i(t))\cdot c^c_{r,i} + k^{mc}_{r,i}(t)\right) + k^{tax}_{r,i}(t) \tag{10}$$

More details on the approach and its justification can be found in Ref. [13].[2]

This modeling approach considers user behavior in four ways: First, it uses individual user driving profiles to determine the BEV fit and electric driving share of a PHEV. These are based on surveys of driving behavior with conventional cars, but allow differences between users' daily and annual driving behavior to be considered. Second, it integrates the WTPM directly from a user survey, but decreases the values from 100% in 2011 to 0% in 2030. This WTPM makes it possible to consider the newness of a technology and to try and determine innovators and early adopters based on [27]. Third, it considers the brand and availability of cars of a certain size with a specific drivetrain. This reduces the market share, but shows a more realistic view of user behavior according to Ref. [29]. Fourth, it uses the cost of individual charging infrastructure as an obstructing factor to EV diffusion.

### 2.4. Comparison of modeling approaches

As the descriptions of the models show, the three analyzed models

[2] To simplify the comparison, some of the symbols in the model description were changed from the reference mentioned.

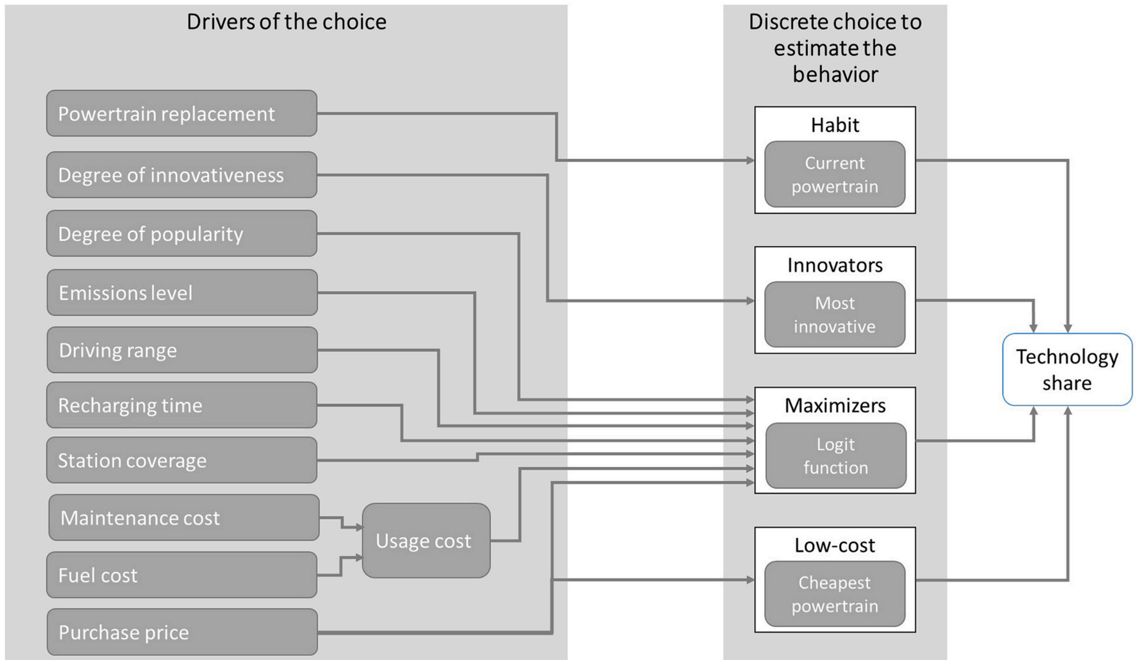


**Fig. 2.** User behavior and linkage to technology share (source: [26], with permission).

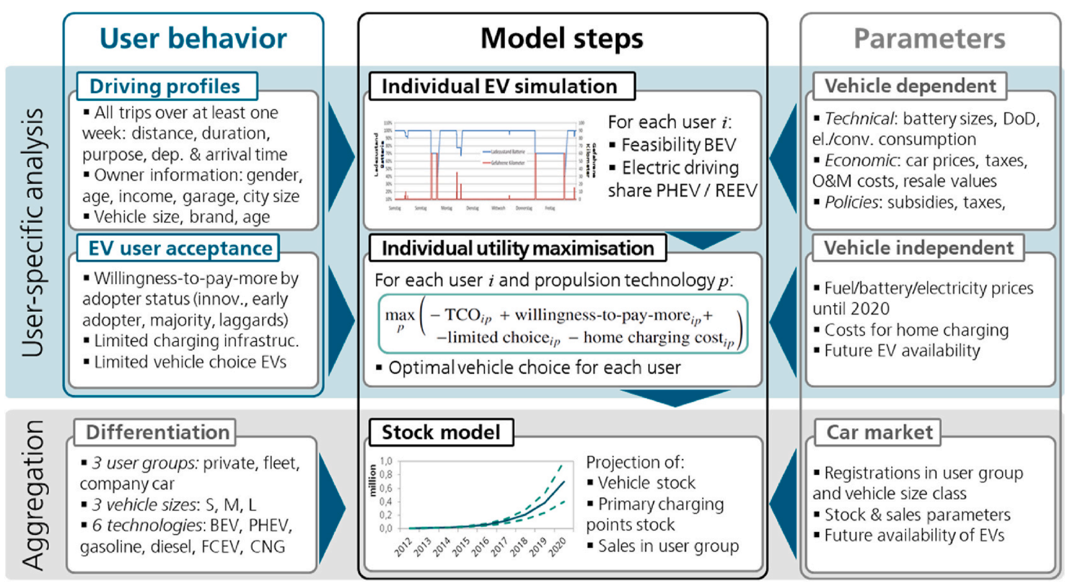


**Fig. 3.** Model overview of ALADIN.

were designed for distinct purposes. As a result, there are several differences in structure and system boundaries between them with respect to user behavior. These are summarized in Table 1.

ASTRA has the highest level of detail regarding vehicle size classes (7) and drivetrains modeled (9) (variable $i$). While there is only one vehicle size class and nine drivetrains in TE3 ($i$), ALADIN distinguishes three vehicle sizes ($r$) and six drivetrains ($i$). The additional three drivetrains in both ASTRA and TE3 compared to ALADIN are biofuel, LPG, and HEV vehicles. HEV are considered implicitly in ALADIN and thus make a comparison of this aspect uncritical. In order to deal with the difference in size classes, vehicle size classes were aggregated and only the overall figures are regarded as comparable.

The buying decision is modeled differently in all three approaches. While ASTRA uses a logit function to determine the market shares of drivetrain technologies (see equations (1) and (2)), ALADIN models individual user behavior with a utility function based on vehicle driving profiles (see equation (6)). The market shares are derived from the cross-sectional analysis. The four user groups in TE3 are comparable to the individual users in ALADIN, but consider different aspects in the buying decision (see Fig. 2). ASTRA and TE3 address the aspect of model choice using a stochastic function, while ALADIN applies a deterministic utility function (see equation (6)).

In addition, the three models have very different approaches to distinguishing groups of users. ASTRA distinguishes two user groups (private and commercial), while there are three user groups in ALADIN (private, commercial fleet vehicles for multiple users, and company cars that can also be used privately) and the four previously mentioned private user types in TE3. These are not distinguished in the results presented in Section 3.

Apart from the different structure and system boundaries, the most

**Table 1**
Overview of modeling approaches.

| Attribute | ASTRA | TE3 | ALADIN |
|---|---|---|---|
| Vehicle size classes (variable *r*) | 7 | 1 | 3 |
| Drivetrains modeled (variable *i*) | 9 | 9 | 6 |
| Buying decision (Equations (1), (2), (6) and (7)) | Logit | Deterministic choice and logit for some | Utility function for individual users |
| User distinction | 2 user groups (private/ commercial) | 4 user groups with 2 types of sales | 3 user groups (private/fleet/ company) with ~7000 driving profiles |
| User behavior integration | Refueling cost function, limited vehicle availability | Complexity of choice varies by user group | Infrastructure cost, WTPM, limited vehicle availability |

**Table 2**
Relevant parameters in the models.

| Input parameter | ASTRA | TE3 | ALADIN |
|---|---|---|---|
| Energy costs [kWh/km] | X | X | X |
| Vehicle data | | | |
| Investment in vehicle [€$_{2018}$] | X | X | X |
| Battery capacity [kWh] | X | X | X |
| Energy consumption factors [kWh/km] | X | X | X |
| OM costs [€$_{2018}$/km] | X | X | X |
| Taxes [€$_{2018}$] | X | X | X |
| Framework parameters | | | |
| Annual car registrations [#] | O | X | X |
| Policy measures (purchase price reduction) [€$_{2018}$] | X | X | X |
| Amortization period and residual value [a] [€$_{2018}$] | X | (–) | X |
| Duration of use [a] | O | (X) | (X) |
| Charging infrastructure [–] | (X) | (X) | (X) |
| Willingness-to-pay-more [% of purchase price] | – | – | X |
| Driving profiles [–] | (–) | (–) | (X) |
| Vehicle availability [–] | (X) | (–)* | (X) |

significant difference between the three models is the integration of individual user behavior. In ASTRA, the refueling cost function (*rc(t)*) distinguishes three non-monetary aspects that vary for alternative drivetrains, i.e. the refueling station density, the need for refueling stations, and the time taken to refuel. These aspects differ largely between drivetrains and the so-called range anxiety of potential car buyers is explicitly considered therewith [30]. The distinction of user groups largely determines the market shares in TE3. Each of these groups follows a specific decision rule (see Fig. 2) that varies in complexity from the simple rules adopted by habit-oriented car purchasers (who stick to their previous drivetrain), innovators (who are keen to test a new one) and low-cost car purchasers (who select the technology with the lowest purchase price) to the more elaborate rules followed by utility maximizers (who consider TCO and popularity). The fourth group is similar to users in ALADIN, although ALADIN considers not only TCO, but also the cost for individual infrastructure (similar to ASTRA) and the WTPM for EVs (equation (4) and (7)). Furthermore, a limited vehicle availability constraint in ALADIN considers the limited brand availability for those users not willing to switch brand (similar to the habit-oriented users in TE3), and the limited vehicle supply in general.

All the models consider obstructing factors that hinder a market diffusion of AFVs, while TE3 and ALADIN also consider the supporting effects and newness of a technology. These aspects were not harmonized in an aligned model run, since they form the core of the three approaches.

## 3. Comparison of model results

### 3.1. Scenario definition

As mentioned in Section 1, the study features one scenario with an aligned input data set and the complete modeling of user behavior to compare the models' results in general, and one scenario which deactivates central aspects of user behavior. The following section presents the harmonized input data and the central aspects of user behavior.

#### 3.1.1. Aligned input data

In order to compare the different model approaches, an aligned input data set is used. Individual parameters are discussed in the following section. Table 2 summarizes the most important parameters and how they are harmonized.

used in model: X, not used in model: , endogenously calculated in model: O

Not harmonized, parameters are printed in brackets.

*As indicated in Section 2.2, powertrain availability is included, but not powertrain model availability.

A common set of energy costs was created and is shown in Table 3. All energy prices are shown without value added tax (VAT).

Energy consumption was also included, measured using the New European Drive Cycle (NEDC) for newly registered vehicles in the Annex. Based on these values, the models determine the real driving consumption individually by multiplying the NEDC-value by vehicle size-specific and drivetrain-specific factors. The Annex also shows the OM costs based on [33]. VAT, car tax and taxation of company cars were also harmonized between the models. An in-depth explanation and justification of the data required for the models can be found in Refs. [20,24,34]. Vehicle investment and battery capacity data are based on a harmonized data set provided by the ASTRA model.

ASTRA, as an impact assessment model, calculates the future annual vehicle registrations for private and company vehicles endogenously based on historical vehicle sales. In order to compare the model results, ALADIN and TE3 use the registration data taken from ASTRA. Since ASTRA includes seven vehicle size classes, sales-weighted data were aggregated for TE3 and ALADIN. The vehicle categories "mini" and "small" were combined to small-sized vehicles, "compact" and "MPV" to medium-sized vehicles, and "middle class", "executive" and "off-road" to large vehicles in the ALADIN model. TE3 does not distinguish between vehicle classes and only uses one aggregated value. The Annex contains an overview of the data.

Policy measures (as effective in summer 2019), e.g. purchase price subsidies, are harmonized between the models.

The amortization period and the residual value have a major influence on the purchase decision for ASTRA and ALADIN. To ensure comparability, all models were run with an amortization period of 10 years and no residual value. This corresponds to the typical duration of first vehicle use of approximately 6 years with residual value [35]. The

**Table 3**
Energy prices without VAT [in €$_{2018}$/kWh].

| Energy carrier type | 2020 | 2025 | 2030 |
|---|---|---|---|
| Gasoline price | 0.154 | 0.188 | 0.201 |
| Diesel price | 0.123 | 0.156 | 0.168 |
| CNG price | 0.065 | 0.069 | 0.071 |
| LPG price | 0.079 | 0.083 | 0.077 |
| Bioethanol price | 0.240 | 0.256 | 0.280 |
| Biodiesel price | 0.120 | 0.125 | 0.134 |
| Hydrogen price | 0.258 | 0.244 | 0.231 |
| Electricity price private | 0.232 | 0.242 | 0.288 |
| Electricity price commercial | 0.150 | 0.154 | 0.181 |

Source: Own calculations based on [31,32].

actual duration of use is not affected and is determined individually for each model.

The remaining categories – modeling of charging infrastructure, driving profiles and vehicle availability – are individual to each model and described in the next section.

#### 3.1.2. Scenario 1: user behavior activated

In addition to a pure TCO calculation, non-monetary factors fundamentally influence the choice of a particular car. ASTRA takes refueling costs into account that reflect infrastructure coverage and the number of refueling actions as well as the availability of car models. Other influencing factors such as brand loyalty, image, design, or perceived safety are not monetarized, but captured by the parameterization of the logit function.

In TE3, charging infrastructure is represented as one of the factors influencing drivetrain choice. As indicated in Section 2.2, driving profiles and powertrain model availability are not modeled. The most important aspect is that user behavior is differentiated into four groups. Table 4 shows the market segmentation for consumers in scenario 1.

ALADIN models user behavior along four dimensions. First, it includes individual charging infrastructure (e. g. in a garage) as an obstructing factor for EVs. Second, it incorporates user brand loyalty, the availability of which is derived from manufacturers' vehicle announcements [11,35]. Third, it includes a willingness-to-pay-more for EVs based on a user survey from 2011, which decreases to 0% by 2030 [11]. Fourth, it includes individual driving behavior based on approximately 7000 vehicle driving profiles [36,37]. The model encompasses a wide range of users by checking the technical and economic feasibility of every single profile. All other parameters can be found in Table Annex 1–4.

#### 3.1.3. Scenario 2: user behavior deactivated

In Scenario 2, all the aspects of user behavior that go beyond a decision based purely on TCO were disabled in ASTRA. More precisely, non-energy-related refueling costs that reflect infrastructure coverage and limited vehicle availability were removed from the decision-making process when choosing a drivetrain.

There is one main difference between scenario 1 and scenario 2 in TE3. This relates to the weight assigned to each consumer group. Specifically, purchase decisions under scenario 2 are made only by the utility maximizers group. In ALADIN, it is not possible to deactivate the profile-specific EV simulation in scenario 2, but all other aspects of user behavior – infrastructure cost, WTPM and limited vehicle availability – are deactivated from 2020 onwards.

### 3.2. Model-based results for scenario 1

The results of all three models for scenario 1 are shown in Fig. 5, which displays newly registered passenger cars (column 1), the passenger car stock (column 2), and the final energy consumption (column 3) for ASTRA (row 1), TE3 (row 2) and ALADIN (row 3).

#### 3.2.1. Results from ASTRA

Total new car registrations are almost stable over time (+1% in 2030 compared to 2020). Electrified drivetrains increase in popularity. In 2030, passenger car registrations of BEVs and PHEVs sum up to 1.3 million registrations (2020: 241,000) accounting for 43% (2020: 8%).

**Table 4**
Market segmentation of vehicle buyer groups [% of the market].

| User Behavior | Habit-oriented | Innovators | Low-cost | Utility maximizers |
|---|---|---|---|---|
| Share of car buyers | 70 | 1 | 5 | 24 |

Source: adapted from [24].

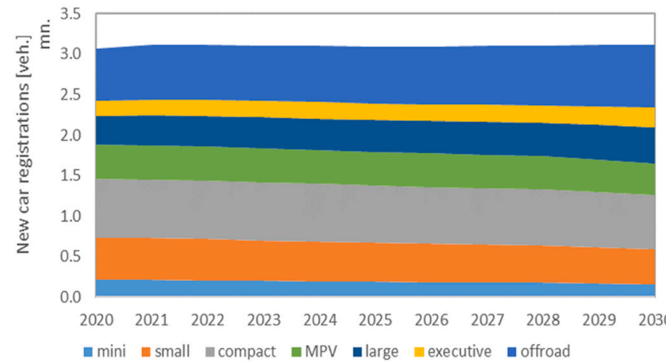


**Fig. 4.** New car registrations based on vehicle size classes (source: ASTRA).

While the share of new PHEV registrations more than triples from 4.6% in 2020 to 17.1% in 2030, the share of BEV registrations increases even more from 3.2% to 25.4%. Especially in the final years of the assessment, the demand for BEVs rises notably. The rise in EV purchases is based on the falling costs of electric drivetrains (e.g. falling battery costs), as well as the expanding charging infrastructure for alternative drives. Both monetary and non-monetary influencing factors play a role in the drivetrain decision-making process.

The total car stock reacts with a reasonable delay to the development of new car registrations. In 2030, the number of electric cars exceeds 6 million (2020: 850,000), accounting for almost 15% of the entire fleet (2020: 2%). Despite falling new registrations, gasoline vehicles still make up the largest share in 2030 (46%), followed by diesel cars (32%). Natural gas vehicles play only a minor role (2%) as limited availability, drivetrain aversion and refueling costs, which are monetarized in ASTRA, outweigh their economic advantages. The stock of FCEV develops slowly (0.2%) due to high costs and limited availability.

The final energy consumption of passenger cars decreases by 23.5% from 397 TWh in 2020 to 303 TWh in 2030. Reasons for the reduction are continuous efficiency improvements for conventional vehicles and a growing share of electric cars. Electric energy consumption of PHEVs (excluding conventional share) and BEVs rises to 17 TWh in 2030 (2020: 2.5 TWh). Despite accounting for 15% of the entire fleet, electric cars need significantly less final energy (7%).

Total tank-to-wheel $CO_2$ emissions decline by almost 30% from 101 Mt in 2020 to 72 Mt $CO_2$ in 2030. PHEVs account for a negligible share of $CO_2$ emissions in 2030 (2%), while BEVs are included with zero tank-to-wheel emissions in the calculation.

#### 3.2.2. Results from TE3

The overall development of total new car registrations is similar to the results from ASTRA. The number of newly registered EVs increases from about 324,000 in 2020 to 881,000 cars in 2030. The share of PHEVs is higher than that of BEVs until 2024 as the charging station density is not as high as in later years. However, the share of BEVs (21%) is higher than the share of PHEVs (8%) in 2030. Since the habit-oriented user group makes up the majority of car buyers, the shift toward newer technologies is slower than in a scenario with decision-making based on pure costs. Stemming from the loss in popularity of diesel cars, there is a shift from diesel to other technologies, in particular to EVs, which is especially visible in 2021. The attractiveness of EVs increases due to more investments in charging infrastructure. Together, newly registered conventional cars add up to about 2.2 million in 2030.

The shift in powertrains is reflected in the overall car stock. In 2020, EVs number nearly half a million vehicles. However, their share rises continuously and reaches 6.5 million EVs in 2030. This is equivalent to more than 15% of the entire vehicle fleet. CNG vehicles play a minor role, but their share remains constant over the years at about 150,000 cars. Other new technologies such as FCEVs do not enter the market.

The final energy consumption of the passenger car stock decreases

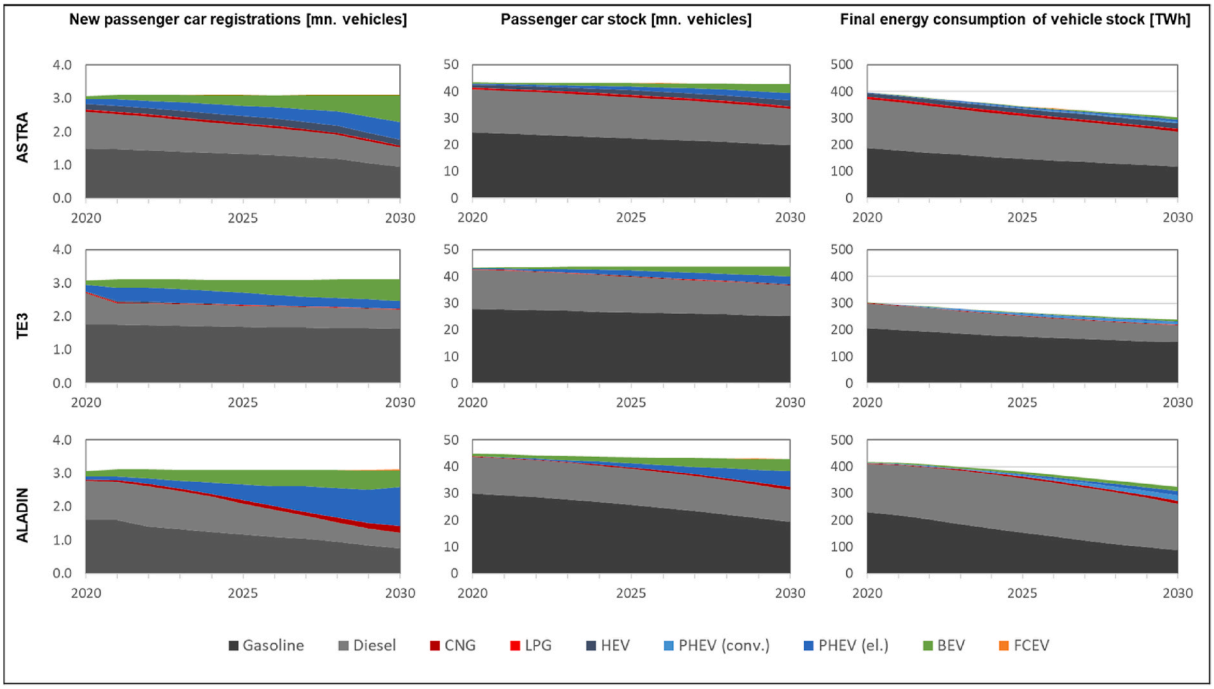


**Fig. 5.** Overview of results of scenario 1 (user behavior activated).

from 303 TWh to 238 TWh between 2020 and 2030. This 21% decrease is due to the fact that more powertrains with lower energy consumption (BEVs, PHEVs) substitute other powertrains with higher energy consumption like diesel or gasoline cars. At the same time, conventional powertrains also become even more efficient and show a decline in energy consumption. The overall low final energy consumption stems from the fact that TE3 assumes the lowest driving range for each car over the year with a value of 12,500 km per year. $CO_2$ emissions decrease from 83 Mt $CO_2$ in 2020 to 63 Mt $CO_2$ in 2030.

#### *3.2.3. Results from ALADIN*

In ALADIN in 2020, the registrations of electric cars account for almost 9% (BEV: 174,000, PHEV: 90,000) of the total registrations. This share rises continuously and reaches about 54% in 2030. While BEV sales almost triple their share from 6% to 16%, the share of PHEVs increases even more, from 3% to 38%, which is different in the other two models. Under the above-mentioned assumptions, it becomes increasingly interesting to replace diesel vehicles with PHEVs. A large number of short trips can be covered electrically at low cost, while the integrated gasoline engine ensures the feasibility of long-distance trips. In this aspect, the model benefits from user-specific modeling of real driving profiles with individual user electric driving shares. However, the user-specific calculation of the electric driving share and the resulting economic efficiency clearly depend on the harmonized battery capacities.

The total car stock follows the development of registrations with a time lag and reaches 10.3 million electric cars in 2030. Of these vehicles, 5.7 million are PHEVs. Although their overall costs are competitive, natural gas vehicles play a minor role. At this point, purchasing a car is not a purely economic decision. To consider user behavior, ALADIN takes the availability of vehicle models and the existing fuel station infrastructure into account. Nevertheless, the stock of natural gas vehicles increases from 0.2 million to 1.1 million in 2030. Additionally, the 2030 stock includes 60,000 FCEV. Due to the high costs and the limited availability of FCEV, there is only a low market diffusion. According to the ALADIN results, the final energy consumption of the passenger car stock decreases from 418 TWh in 2020 to 325 TWh in 2030. This reduction is achieved through continuous efficiency improvements of the vehicles and a growing number of electric cars within the fleet. While the share of electric energy consumption in 2020 is negligible, electric energy consumption of vehicles accounts for 31 TWh in 2030. This corresponds to a $CO_2$ reduction (tank-to-wheel) from 110 Mt $CO_2$ in 2020 to 77 Mt $CO_2$ in 2030.

### *3.3. Model-based results for scenario 2*

In the second scenario, user behavior was deactivated in all three models where possible (see Section 3.1.3). The results of all three models for scenario 2 are shown in Fig. 6. Here, the new passenger car registrations (column 1), the passenger car stock (column 2) and the final energy consumption (column 3) are shown for ASTRA (row 1), TE3 (row 2) and ALADIN (row 3).

#### *3.3.1. Results from ASTRA*

The overall number of new car registrations declines slightly over time (−6% in 2030 compared to 2020) and is slightly lower than in Scenario 1 (2025: −4.9%, 2030: −6.8%). The reason is that, without non-economic user behavior, consumers are more open to alternative drivetrains and replace their cars earlier. Both gas-powered and electrified drivetrains increase in popularity as refueling issues, i.e. infrastructure coverage, and limited vehicle availability are disregarded. In 2030, passenger car registrations of PHEV and BEV increase by 16.7% and 11.1%, respectively, in comparison to Scenario 1. Above all, however, the demand for natural gas vehicles increases sharply with 2.7 million additional new registrations of CNG cars and 3.1 million new registrations of LPG cars in 2030. This shows that natural gas vehicles are an economically reasonable alternative if a decision is based solely on TCO, and users are no longer restricted by a lack of infrastructure or vehicle availability.

The described changes in new registrations are also reflected in a changed fleet composition. In 2030, electric cars amount to almost 10 million (4.7 million PHEV, 5.0 million BEV), accounting for 23% of the entire fleet (2020: 2%). Together, CNG and LPG account for 16% of the total stock in 2030. Despite the increased popularity of alternative cars, gasoline vehicles still constitute the largest share in 2030 (32%), followed by diesel-powered cars (26%). FCEVs are still too costly for significant market diffusion.

The final energy consumption of passenger cars decreases over time from 397 TWh in 2020 to 308 TWh in 2030, but is slightly higher than in

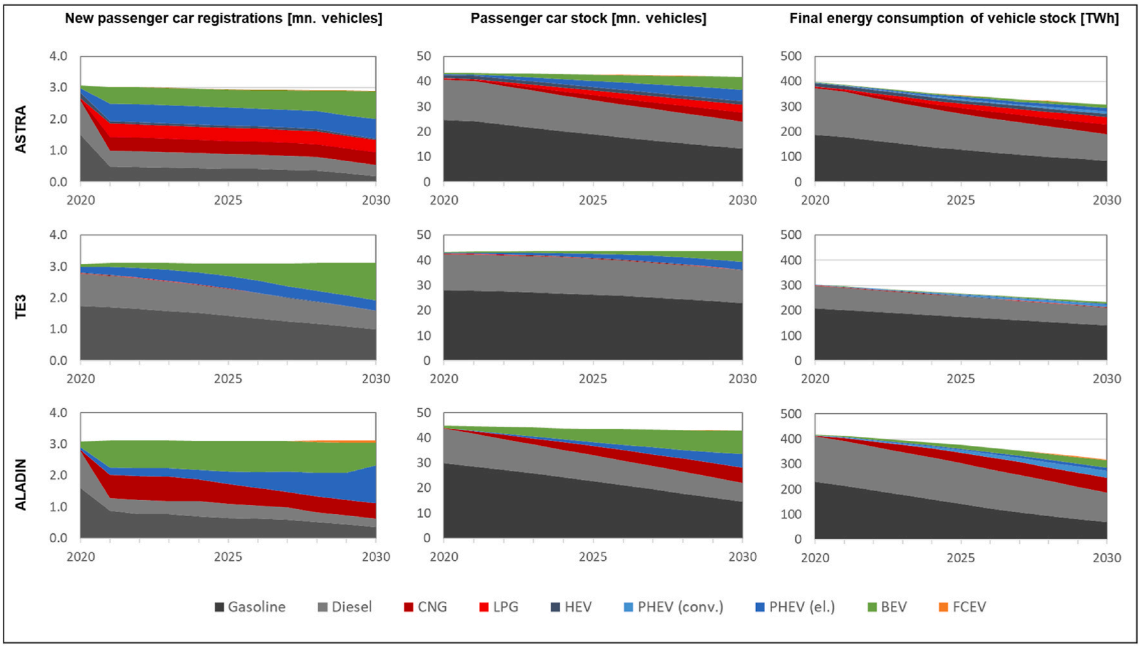


**Fig. 6.** Overview of results of scenario 2 (user behavior deactivated).

Scenario 1 (303 TWh in 2030). This is caused by a slight increase in annual mileage, and the sharp increase in the energy consumption of natural gas vehicles accompanied by a slight increase in electricity demand (due to an increased number of electrified cars) that offset the decrease in the energy consumption of conventional cars. However, total tank-to-wheel $CO_2$ emissions decline by −35% from 101 Mt in 2020 to 65 Mt in 2030 and are lower (−10%) than in Scenario 1 (72 Mt in 2030).

### 3.3.2. *Results from TE3*

As TE3 uses the harmonized vehicle registrations from ASTRA, the number of total new car registrations and the total passenger car stock are the same. However, the vehicle fleet composition is different to Scenario 1. There is a strong uptake of EVs, which increase from about 271,000 registrations in 2020 to 1,506,000 in 2030. Hence, nearly every second car sold in 2030 is an EV. BEVs experience a particularly strong increase and their share in registrations rises from 3% (93,000 BEVs) to 38% (1,190,000 BEVs) in 2030. PHEVs have a higher share than BEVs until 2024, as charging station density is still low to start with. The PHEV share almost doubles from 5.8% to 10.2%. The shift in powertrains is reflected in the overall car stock. In 2020, EVs account for over half a million of the total car stock. However, this share continues to rise and reaches 7.45 million EVs in 2030, equivalent to more than 17% of the entire vehicle fleet. Disregarding habit-oriented consumers accelerates the shift in stock from conventional cars to electric cars in scenario 2. It is therefore not surprising that there are roughly one million additional EVs in 2030 in scenario 2. Among the other alternative car technologies, CNG and LPG vehicles play an even smaller role in scenario 2 than in scenario 1. Here, the formerly habit-oriented users switch to EVs based on economic considerations. Again, FCEVs do not enter the market, as they are too costly.

The final energy consumption of the passenger car stock decreases from 303 TWh to 234 TWh between 2020 and 2030. This 23% decrease results from an increased number of powertrains with lower energy consumption (BEVs, PHEVs) that replace other powertrains with higher energy consumption, like diesel or gasoline cars. At the same time, however, conventional powertrains also become more efficient and show decreased energy consumption. The overall low final energy consumption in this model is due to the fact that TE3 assumes the lowest annual vehicle kilometers traveled with 12,500 km per year. $CO_2$ emissions fall from 83 Mt $CO_2$ in 2020 to 62 Mt $CO_2$ in 2030 (a decrease of 25%).

### 3.3.3. *Results from ALADIN*

In scenario 2, the share of electric car sales in 2020 is identical with scenario 1 and accounts for 9% of the market. After 2020, EV sales increase significantly due to the deactivation of user behavior. In 2021, their share is already 35%. Thus, without restrictions due to infrastructure and the limited availability of consumers' favorite brands, EVs would be the most economical alternative for 35% of drivers. This share increases to 62% in 2030. While BEVs almost quadruple their share from 6% to 23%, PHEVs increase more than tenfold, from 3% to 39%. Once again, this is due to the high driving range of PHEVs and their lower costs compared to BEVs. The share of natural gas vehicles also increases significantly, from 1% in 2020 to 16% in 2030, with a peak of 25% in 2023. In particular, gasoline and diesel vehicles are replaced by the less expensive CNG vehicles, as users are no longer restricted in terms of the available models or infrastructure.

There are 9.2 million BEVs and 5.4 million PHEVs in 2030. CNG vehicles display a similar trend to PHEVs, and reach a stock of 5.9 million vehicles in 2030. FCEVs play a subordinate role in scenario 2. Even in scenario 1, they are too expensive for market diffusion.

In scenario 2, the final energy consumption of the passenger car stock decreases from 418 TWh in 2020 to 319 TWh in 2030. The difference compared to scenario 1 is due to the higher share of EVs. The electric energy consumption rises to 42 TWh in 2030. The $CO_2$ emissions (tank-to-wheel) drop from 110 Mt in 2020 to 57 Mt in 2030.

## 3.4. *Comparison of models*

Fig. 7 compares the vehicle registration results of the individual models to draw conclusions about the models' characteristics. A summary of the main results can be found in Table Annex 5 and Table Annex 6.

ASTRA shows an increase in demand for both natural gas and electrified drivetrains if refueling issues, i.e. infrastructure coverage and limited vehicle availability, are disregarded. In 2030, the share of gas-powered cars in the total fleet is 16% (2% in scenario 1) and the share of electrified cars accounts for 23% (14% in scenario 1). Thus, if the

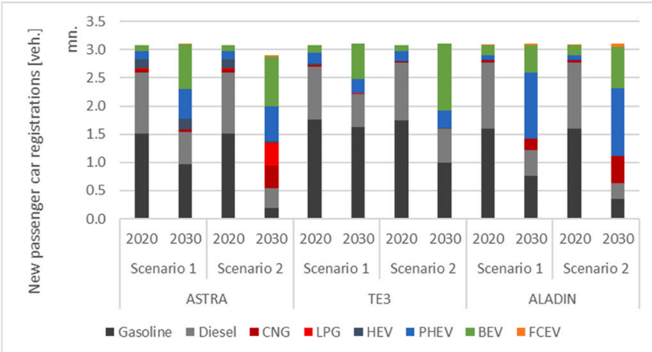


**Fig. 7.** Comparison of new car registrations.

purchase decision is based solely on TCO and users are no longer restricted by charging infrastructure and vehicle availability, alternative vehicles are an economically reasonable option.

TE3 shows an increase in EV registrations from 28% (scenario 1) to 48% in 2030 (scenario 2). In scenario 1, which considers user behavior, habit-oriented users in particular inhibit the diffusion of EVs compared to a decision based purely on cost in scenario 2. CNG and LPG vehicles barely appear in either scenario. Their diffusion is essentially limited by the calibrated logit function and not modeled as part of the four user groups.

ALADIN shows significant differences in new EV registrations between the scenarios. Without limiting user behavior, their share increases from 54% to 64% in 2030. The difference reaches the maximum of 24% points in 2021 and decreases continuously thereafter. In scenario 1, brand loyalty, which encounters low model availability from various manufacturers, and the limited infrastructure have a particularly inhibiting effect on EV diffusion. The WTPM in scenario 1 can only compensate this effect to a limited extent. CNG vehicles play a significantly larger role in scenario 2, accounting for 16% of new registrations in 2030. This corresponds to an increase of 10% points compared to scenario 1, also caused by neglecting brand loyalty.

When comparing the models with each other, the agent-based model ALADIN shows the clearest response to deactivating user behavior. While discrete choice models still include some parts of user behavior in the calibrated determination of the vehicle choice parameters (parameters $\alpha$ and $\beta$ in ASTRA or $\alpha,\ \beta,\ \gamma,\ \delta,\ \varepsilon$ and $\theta$ in TE3), agent-based models can represent the techno-economic purchase decision completely independently of user behavior.

With regard to the split between BEVs and PHEVs, ALADIN shows significantly higher PHEV shares than TE3 and ASTRA. This can be attributed to user behavior, too: ALADIN calculates the electric driving share individually for each user or for each driving profile, while TE3 and ASTRA consider an average value and model a more general decision. Since this basic user behavior cannot be deactivated in ALADIN, it occurs in both scenarios.

Finally, the difference in CNG and LPG vehicle modeling between the two discrete choice models is also noteworthy. While ASTRA follows ALADIN in scenario 2 and generates a high number of new registrations due to cost advantages, these are almost constant in both scenarios in TE3. This clearly reveals the models' different use of vehicle choice parameters.

## 4. Findings, limitations and further research

In this paper, three models of the diffusion of AFVs in the German market were compared in detail, with a focus on user behavior. A qualitative comparison of the modeling approaches was performed in Section 2, followed by two model runs with and without user behavior.

The models have very different approaches to including user behavior. The consideration of different user groups, charging infrastructure, and annual mileage is completely different in the three models: (i) ASTRA distinguishes commercial and private vehicle buyers into seven size classes; ALADIN differentiates between three user groups (private, commercial fleet, company cars) and three size classes; TE3 has four car buyer groups without differentiating car size. (ii) All three models include the cost for charging infrastructure, but the necessity to detour for charging is user-specific in ALADIN and drivetrain-specific in TE3 and ASTRA. (iii) The differences in annual mileage are considered via the logit functions in TE3 and ASTRA, and via the individual users in ALADIN. Including individual user data (as in ALADIN) makes it possible to study the effects on specific user (groups) in more detail, but requires a large amount of input data and long computation times. Effects on individual users are easier to study this way. The consideration of individual vehicle buyers in ALADIN (agent-based model) is helpful to understand the effects of changes to the model when compared to the more aggregated logit-based approach in ASTRA and TE3 (system dynamics models). However, more general effects like changes in population or income can be better explained in ASTRA and TE3. These were not part of this study. Hence, when choosing a model, it is important to think about the causal relations and to select the appropriate model depending on the research focus and interdependencies.

In all the models, it was found that obstructing factors have a greater effect than supporting ones, in other words, that the integration of user behavior reduces the number of EVs in the models. Comparing this to studies of user acceptance in this field, this seems a reasonable effect at an early stage of EV diffusion, and should diminish over time [38]. Both scenarios show large market shares of electric cars in Germany in the next few years (30–50% of new vehicle registrations in 2030). Independent of the parameters in scenarios 1 and 2, the simulations show an increase in electric car sales, thereby altering the car stock composition in the coming years. This is accompanied by a significant decrease in the final energy demand of German passenger cars by 2030 (20–25%). PHEVs may be more than just an interim solution until 2030. In both scenarios, the share of PHEVs in new EV registrations is at least 21% (in ASTRA, ALADIN, and TE3), and even 73% in scenario 2 for ALADIN. These results were obtained using very different modeling approaches, but – apart from the PHEV share – are very similar and can thus be considered robust. The difference in the PHEV vs. BEV share results from a fixed (ASTRA, TE3) vs. variable (ALADIN) electric driving share as well as how the models include range anxiety and charging infrastructure. The increasing ranges of BEVs are considered sufficient for the users in all three models, as BEVs are the preferred option in 2030.

There are many different approaches to modeling the market diffusion of alternative fuels in transport. Numerous models exist and they all offer different insights, but it is often difficult to compare them. The three models analyzed in this paper cover many of the aspects considered important by several models, such as the inclusion of charging infrastructure, range anxiety, or individual user behavior [8]. However, other user behavioral aspects could be included and studied and studied, e. g. neighboring effects, environmental attitude or other ways of including range anxiety [30,39].

Other factors like the purchase price and operating cost are also mentioned as important aspects in Ref. [5]. Earlier publications of TE3 assigned importance to purchase price subsidies, investment in charging infrastructure, and $CO_2$ emission standards [23,24]. Similar aspects were also mentioned in ASTRA [40], especially bonus-malus regulation [41]. Earlier publications of ALADIN identified private and charging infrastructure at work and energy prices as key parameters for EV market diffusion [42,43]. Changes to vehicle parameters, energy prices and new vehicle registrations would also have a meaningful impact on the results and were not analyzed in this paper. However, the focus here was on exploring the differences between including and excluding user behavioral aspects based on an aligned input data set. It would be especially interesting to determine and then compare the impact that hard and soft factors have, e.g. cost vs. user behavior.

Future research could compare the results and conclusions of this paper with other studies that consider two aspects: (i) other models of the German market based on simulation methods (e.g. Refs. [8,11,44]); (ii) models based on other methods, such as energy optimization models in which energy prices are endogenously determined [45]. Further research is also needed on the integration of psychological factors in these types of model, while acknowledging that such factors are harder to quantify than techno-economic ones. Applying the models to other vehicle markets could provide additional valuable insights, as some assumptions that influence the results could be country-specific.

## Credit author statement

Till Gnann: Conceptualization; Funding acquisition; Investigation; Methodology; Project administration; Resources; Supervision; Validation; Visualization; Writing – original draft; Writing – review & editing. Daniel Speth: Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Writing – original draft; Writing – review & editing. Katrin Seddig: Data curation; Investigation; Methodology; Software; Validation; Visualization; Writing – original draft; Writing – review & editing. Meike Stich: Data curation; Investigation; Methodology; Software; Validation; Visualization; Writing – original draft; Writing – review & editing. Wolfgang Schade: Data curation; Funding acquisition; Resources; Supervision; Writing – review & editing. Jonatan J. Gómez Vilchez: Data curation; Methodology; Software; Supervision; Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The views expressed are purely those of the authors and may not under any circumstances be regarded as stating the official position of the European Commission.

## Annex.

**Table Annex 1**
Vehicle investment for private vehicles [€$_{2018}$] without VAT

| Vehicle size | 2020 | 2025 | 2030 |
|---|---|---|---|
| Mini | | | |
| Gasoline | 10,908 | 10,989 | 11,152 |
| Diesel | 12,092 | 12,012 | 12,119 |
| Compressed natural gas | 12,324 | 11,907 | 11,759 |
| Liquefied petroleum gas | 14,898 | 14,743 | 14,386 |
| Hybrid | 12,209 | 12,114 | 11,856 |
| Plug-in hybrid | 14,699 | 14,231 | 13,529 |
| Fully electric | 15,170 | 14,921 | 13,817 |
| Fuel cell | 18,760 | 17,123 | 15,570 |
| Small | | | |
| Gasoline | 15,458 | 15,602 | 15,841 |
| Diesel | 17,521 | 17,483 | 17,706 |
| Compressed natural gas | 16,810 | 16,367 | 16,191 |
| Liquefied petroleum gas | 20,422 | 20,319 | 20,002 |
| Hybrid | 16,760 | 16,641 | 16,238 |
| Plug-in hybrid | 19,870 | 19,332 | 18,359 |
| Fully electric | 20,633 | 20,111 | 18,753 |
| Fuel cell | 24,601 | 22,676 | 20,830 |
| Compact | | | |
| Gasoline | 23,175 | 23,421 | 23,795 |
| Diesel | 24,703 | 24,682 | 25,016 |
| Compressed natural gas | 24,502 | 23,993 | 23,774 |
| Liquefied petroleum gas | 27,608 | 27,622 | 27,253 |
| Hybrid | 24,361 | 24,205 | 23,650 |
| Plug-in hybrid | 28,203 | 27,609 | 26,373 |
| Fully electric | 28,532 | 27,441 | 26,003 |
| Fuel cell | 32,575 | 30,353 | 27,975 |
| Large | | | |
| Gasoline | 32,570 | 32,970 | 33,541 |
| Diesel | 37,667 | 37,765 | 38,425 |
| Compressed natural gas | 34,598 | 34,030 | 33,786 |
| Liquefied petroleum gas | 41,730 | 41,974 | 41,698 |
| Hybrid | 34,205 | 34,027 | 33,495 |
| Plug-in hybrid | 39.238 | 38,594 | 37,368 |
| Fully electric | 40,506 | 40,229 | 38,562 |
| Fuel cell | 45,864 | 43,296 | 40,390 |
| Executive | | | |
| Gasoline | 57,445 | 58,201 | 59,264 |
| Diesel | 55,986 | 56,050 | 56,902 |
| Compressed natural gas | 58,960 | 58,122 | 57,774 |
| Liquefied petroleum gas | 57,416 | 57,849 | 57,735 |

(continued on next page)

**Table Annex 1** (*continued*)

| Vehicle size | 2020 | 2025 | 2030 |
|---|---|---|---|
| Mini | | | |
| Hybrid | 57,502 | 57,214 | 56,438 |
| Plug-in hybrid | 62,559 | 61,779 | 60,146 |
| Fully electric | 60,595 | 59,803 | 57,617 |
| Fuel cell | 65,785 | 62,570 | 59,442 |
| Off-road | | | |
| Gasoline | 20,422 | 20,319 | 20,002 |
| Diesel | 21,965 | 21,012 | 20,110 |
| Compressed natural gas | 25,445 | 25,238 | 24,755 |
| Liquefied petroleum gas | 23,175 | 23,421 | 23,795 |
| Hybrid | 20,633 | 20,111 | 18,753 |
| Plug-in hybrid | 24,348 | 22,999 | 21,410 |
| Fully electric | 24,361 | 24,205 | 23,650 |
| Fuel cell | 27,667 | 26,637 | 25,912 |
| MPV (Multi-Purpose Vehicle) | | | |
| Gasoline | 27,608 | 27,622 | 27,253 |
| Diesel | 29,084 | 28,125 | 27,008 |
| Compressed natural gas | 37,169 | 36,908 | 36,269 |
| Liquefied petroleum gas | 31,988 | 32,389 | 32,954 |
| Hybrid | 28,532 | 27,441 | 26,003 |
| Plug-in hybrid | 32,986 | 30,989 | 28,628 |
| Fully electric | 33,691 | 33,523 | 33,023 |
| Fuel cell | 39,208 | 37,878 | 36,999 |

Source: Own estimations, based on [43].

Commercial vehicles tend to be cheaper than private vehicles, but the general trend is identical.

**Table Annex 2**
Costs for O&M [$€_{2018}$/km] without VAT

| Vehicle size | 2020 | 2025 | 2030 |
|---|---|---|---|
| Small | | | |
| Gasoline | 0.026 | 0.026 | 0.026 |
| Diesel | 0.026 | 0.026 | 0.026 |
| Compressed natural gas | 0.030 | 0.030 | 0.030 |
| Liquefied petroleum gas | 0.030 | 0.030 | 0.030 |
| Hybrid | 0.025 | 0.025 | 0.025 |
| Plug-in hybrid | 0.023 | 0.023 | 0.023 |
| Fully electric | 0.018 | 0.018 | 0.018 |
| Fuel cell | 0.038 | 0.038 | 0.038 |
| Medium | | | |
| Gasoline | 0.048 | 0.048 | 0.048 |
| Diesel | 0.048 | 0.048 | 0.048 |
| Compressed natural gas | 0.055 | 0.055 | 0.055 |
| Liquefied petroleum gas | 0.055 | 0.055 | 0.055 |
| Hybrid | 0.046 | 0.046 | 0.046 |
| Plug-in hybrid | 0.043 | 0.043 | 0.043 |
| Fully electric | 0.033 | 0.033 | 0.033 |
| Fuel cell | 0.071 | 0.071 | 0.071 |
| Large | | | |
| Gasoline | 0.074 | 0.074 | 0.074 |
| Diesel | 0.074 | 0.074 | 0.074 |
| Compressed natural gas | 0.085 | 0.085 | 0.085 |
| Liquefied petroleum gas | 0.085 | 0.085 | 0.085 |
| Hybrid | 0.070 | 0.070 | 0.070 |
| Plug-in hybrid | 0.066 | 0.066 | 0.066 |
| Fully electric | 0.051 | 0.051 | 0.051 |
| Fuel cell | 0.109 | 0.109 | 0.109 |

Source: Own estimations, based on [33].

**Table Annex 3**
Energy consumption (new European drive cycle) of newly registered vehicles [kWh/km]

| Vehicle size | 2020 | 2025 | 2030 |
|---|---|---|---|
| Mini | | | |
| Gasoline | 0.350 | 0.306 | 0.306 |
| Diesel | 0.362 | 0.311 | 0.289 |
| Compressed natural gas | 0.326 | 0.326 | 0.326 |
| Liquefied petroleum gas | 0.358 | 0.330 | 0.330 |

(continued on next page)

**Table Annex 3** (*continued*)

| Vehicle size | 2020 | 2025 | 2030 |
|---|---|---|---|
| Mini | | | |
| Hybrid | 0.296 | 0.291 | 0.291 |
| Plug-in hybrid | 0.197 | 0.180 | 0.166 |
| Fully electric | 0.093 | 0.085 | 0.078 |
| Fuel cell | 0.170 | 0.155 | 0.143 |
| Small | | | |
| Gasoline | 0.366 | 0.316 | 0.306 |
| Diesel | 0.299 | 0.299 | 0.299 |
| Compressed natural gas | 0.491 | 0.449 | 0.414 |
| Liquefied petroleum gas | 0.427 | 0.368 | 0.352 |
| Hybrid | 0.345 | 0.301 | 0.301 |
| Plug-in hybrid | 0.201 | 0.184 | 0.170 |
| Fully electric | 0.108 | 0.099 | 0.091 |
| Fuel cell | 0.198 | 0.181 | 0.167 |
| Compact | | | |
| Gasoline | 0.408 | 0.351 | 0.315 |
| Diesel | 0.350 | 0.301 | 0.299 |
| Compressed natural gas | 0.426 | 0.426 | 0.426 |
| Liquefied petroleum gas | 0.378 | 0.373 | 0.373 |
| Hybrid | 0.401 | 0.343 | 0.320 |
| Plug-in hybrid | 0.231 | 0.211 | 0.195 |
| Fully electric | 0.126 | 0.115 | 0.106 |
| Fuel cell | 0.230 | 0.210 | 0.194 |
| Large | | | |
| Gasoline | 0.469 | 0.404 | 0.369 |
| Diesel | 0.386 | 0.359 | 0.359 |
| Compressed natural gas | 0.920 | 0.840 | 0.775 |
| Liquefied petroleum gas | 0.445 | 0.415 | 0.415 |
| Hybrid | 0.474 | 0.406 | 0.348 |
| Plug-in hybrid | 0.266 | 0.243 | 0.224 |
| Fully electric | 0.149 | 0.136 | 0.125 |
| Fuel cell | 0.272 | 0.248 | 0.229 |
| Executive | | | |
| Gasoline | 0.652 | 0.561 | 0.474 |
| Diesel | 0.481 | 0.418 | 0.418 |
| Compressed natural gas | 0.614 | 0.614 | 0.614 |
| Liquefied petroleum gas | 0.979 | 0.888 | 0.749 |
| Hybrid | 0.578 | 0.495 | 0.423 |
| Plug-in hybrid | 0.359 | 0.328 | 0.303 |
| Fully electric | 0.201 | 0.183 | 0.169 |
| Fuel cell | 0.331 | 0.302 | 0.279 |
| Off-road | | | |
| Gasoline | 0.479 | 0.412 | 0.396 |
| Diesel | 0.466 | 0.401 | 0.379 |
| Compressed natural gas | 1.132 | 1.088 | 1.005 |
| Liquefied petroleum gas | 0.499 | 0.499 | 0.499 |
| Hybrid | 0.514 | 0.440 | 0.404 |
| Plug-in hybrid | 0.308 | 0.287 | 0.265 |
| Fully electric | 0.199 | 0.191 | 0.176 |
| Fuel cell | 0.295 | 0.269 | 0.248 |
| MPV (Multi-Purpose Vehicle) | | | |
| Gasoline | 0.440 | 0.379 | 0.369 |
| Diesel | 0.464 | 0.400 | 0.359 |
| Compressed natural gas | 0.589 | 0.589 | 0.589 |
| Liquefied petroleum gas | 0.466 | 0.436 | 0.436 |
| Hybrid | 0.439 | 0.395 | 0.395 |
| Plug-in hybrid | 0.261 | 0.238 | 0.220 |
| Fully electric | 0.138 | 0.126 | 0.116 |
| Fuel cell | 0.252 | 0.230 | 0.212 |

Source: Own estimations, based on [46].

**Table Annex 4**
Battery capacity [kWh] for battery electric cars

| Vehicle size | 2020 | 2025 | 2030 |
|---|---|---|---|
| Mini | 17.6 | 17.6 | 17.6 |
| Small | 17.6 | 17.6 | 17.6 |
| Compact | 47.5 | 55.0 | 60.0 |
| Large | 47.5 | 55.0 | 60.0 |
| Executive | 97.5 | 100.0 | 100.0 |
| Offroad | 97.5 | 100.0 | 100.0 |
| MPV | 47.5 | 55.0 | 60.0 |

Source: Own assumptions based on [20].

**Table Annex 5**
Summary of results in scenario 1 for all models

| Scenario 1 | ASTRA | | TE3 | | ALADIN | |
|---|---|---|---|---|---|---|
| | 2020 | 2030 | 2020 | 2030 | 2020 | 2030 |
| EV sales | 241,000 | 1,324,000 | 324,000 | 881,000 | 264,000 | 1,668,000 |
| EV stock | 850,000 | 6,133,000 | 488,000 | 6,521,000 | 978,000 | 10,315,000 |
| Energy [TWh] | 397 | 303 | 303 | 238 | 418 | 325 |
| Electricity [TWh] | 2 | 16 | 0.7 | 9.1 | 3 | 31 |
| Emissions [Mt$CO_2$] | 101 | 72 | 83 | 63 | 110 | 77 |

Source: Own calculations

**Table Annex 6**
Summary of results in scenario 2 for all models

| Scenario 2 | ASTRA | | TE3 | | ALADIN | |
|---|---|---|---|---|---|---|
| | 2020 | 2030 | 2020 | 2030 | 2020 | 2030 |
| EV sales | 241,000 | 1,501,000 | 271,000 | 1,507,000 | 264,000 | 1,930,000 |
| EV stock | 850,000 | 9,706,000 | 524,000 | 7,447,000 | 978,000 | 14,688,000 |
| Energy [TWh] | 397 | 308 | 303 | 234 | 418 | 319 |
| Electricity [TWh] | 2 | 28 | 0.7 | 10.7 | 3 | 42 |
| Emissions [Mt$CO_2$] | 101 | 65 | 83 | 62 | 110 | 57 |

Source: Own calculations

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