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Modelling Market Diffusion of Electric
Vehicles with Real World Driving Data

Part I: Model Structure and Validation

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Abstract

The future market diffusion of electric vehicles (EVs) is of great importance for transport related green house gas emissions and energy demand. But most studies on the market diffusion of EVs focus on average driving patters and neglect the great variations in daily driving of individuals present in real-world driving data. Yet these variations are important for EVs since range limitations and the electric driving share of plug-in hybrids strongly impact the economic evaluation and consumer acceptance. Additionally, studies often focus on private cars only and neglect that commercial buyers account for relevant market shares in vehicle sales. Here, we propose a reliable, user specific model for the market diffusion of EVs and evaluation of EV market diffusion policies based on real world driving data. The data and model proposed include both private and commercial users in Germany and allow the calculation of realistic electric driving shares for all usage patterns. The proposed model explicitly includes user heterogeneity in driving behaviour, different user groups, psychological aspects and the effect of charge-at-home options. Our results show that the proposed model reproduces group specific market shares, gives confidence bands of market shares and reliably simulates individual electric driving shares.

Contents

1 Introduction

Global warming and the increase of greenhouse gas (GHG) emissions are some of the most fundamental challenges of the 21st century [1, 2]. Especially the transport sector with a growing number of vehicles worldwide has to make a contribution to reduce GHG emissions radically. Furthermore, the scarcity of conventional energy resources, in particular crude oil, requires new energy carriers in the transport sector. Electric vehicles (EVs) such as battery (BEV), plug-in hybrid (PHEV) or range extended EVs (REEV) are a means to this problem since they are more energy efficient than conventional cars and produce less GHG emissions when renewable energy is used [2].

There are several studies and models describing the introduction and market diffusion of EVs and studying the effect of policies stimulating EV market diffusion. Most of these studies focus on average driving patters [3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. This could give incorrect results, since individual driving patterns show great variations both between different users as well as between different days for individual users [13, 14]. This is of particular relevance for electric vehicles for which range limitations and electric driving shares have a high impact on the economic evaluation and consumer acceptance. Additionally, these studies often focus only on private cars and neglect that commercial buyers have a relevant market share on selling figures of new vehicles. Their purchase decision is also different, e.g. the cost-effectiveness is more important for fleet applications than for private buyers. Furthermore, the average vehicle kilometres travelled (VKT) of commercial car users are much higher than of private car users.

The present paper attempts to elaborate and assess a reliable, user-specific model for market diffusion of EVs and the evaluation of policies influencing EV market diffusion. User-specific in the sense that all relevant buyer groups are represented with their specific purchase behaviour and individual driving patterns. The developed multi agent-based simulation model is applied to and evaluated for Germany with a time horizon until 2020.

In the following section 2 an overview of existing models for EV market diffusion is given, motivating the development of a new model. In section 3 the simulation model is described including a critical discussion of the model. Selected results and different model validations are presented in section 4. In the final section 5 a summary and conclusions are given. A further application of the model with different market diffusion scenarios for Germany until 2020 will be developed in [15].

2 Existing Models of Electric Vehicle Market Diffusion

The diffusion of new technologies and EVs in particular has received considerable attention in the literature (see [16] for a recent review of EV market

diffusion models). A general classification of market diffusion models was given by Geroski [17]. He describes two groups of models for market diffusion of innovations: population and probit models. We will discuss them briefly and classify existing market diffusion models accordingly in order to categorise the model proposed here.

Population models describe users or adopters not as individuals, but as groups. Population models are epidemic models which assume that the rate of adoption is proportional to the number of adopters and the remaining population that has not adopted a technology yet. This leads to the well-known logistic differential equation and can be interpreted via the spread of information about a technology [17]. We find population models for EV market diffusion or market diffusion of other alternative fuel vehicles, in [18, 19, 5, 6, 7, 8, 9, 10, 11], which range from simple mathematical equations to complex system dynamics models.

Population models offer a simple structure and interpretation. They are usually applied by calibrating the market diffusion curve to existing market data or by assuming hypothetical growth rates. This procedure is rather sensitive in early market phases when little data is available. Furthermore, the heterogeneity of the individual buying decisions and preferences of users, for example reflected in the willingness to pay more for new technologies of some users, as well as the individual economics of the driving behaviour cannot be incorporated into these models.

The second group of market diffusion models, probit and agent-based models, studies adopters individually. These models are often applied when the purchase decision is more complex or the technologies to be adopted are expensive. For example, a simple probit model for EV adoption would calculate the average ownership cost difference between conventional and electric vehicles and estimate an EV market share based on this difference. As fuel and battery prices change over time, these cost differences change and with them the estimated EV market share. Thus, probit models develop market diffusion bottom-up and acknowledge that individual users can be very different. Probit models were used to model EV market diffusion in [20, 21, 22, 23, 24] where the detailed modelling approaches range from determining user shares by stated preference experiments to agent-based models. Furthermore, there is a third group of hybrid models which try to combine population and agent-based modelling approaches [25, 12, 26, 27].

In probit models, actual user behaviour was studied in [21, 22, 23, 24] and some models are based on actual driving behaviour [21, 22]. This would in principle allow to analyse user behaviour in more detail. However, the latter models use driving profiles of only one day which can cause severe inaccuracies on the individual level as a single day might not show the individual's typical driving as is crucial for EVs due to their limited range (see [28] and section 4.3).

Consumer choice models are a third class of models to analyse the market diffusion of electric vehicles [16]. However, these models face the problem that consumer statements about their preferences for EVs are often inaccurate.

Given the current market shares of EVs, the vast majority of users has never experienced an EV and can hardly judge its utility. For example, in trying to predict the utility of a new mode of transport by discrete choice methods, reference [29, p. 177] concludes that the use-value of attributes of a new mode cannot be estimated from the existing modes if the the former exhibits some important attributes which none of the old ones has. This is certainly the case for EVs and pinpoints the limitations of consumer choice models for EV market diffusion when they are based on surveys with users of conventional vehicles.

In summary, agent-based models offer the possibility to include several aspects of great relevance for the market diffusion of EVs: individual purchase preferences, individual driving behaviour (to account for the limited range of EVs and the vehicle kilometres travelled (VKT) related usage costs), the need for frequent recharging and infrastructure as well as the limited choice of EV brands and models. In the model proposed here and coined ALADIN (**Al**ternative **A**utomobiles **D**iffusion and **In**frastructure) we explicitly take these factors into account in an agent-based model with different user groups and their individual decision making processes.

3   Proposed Model for EV Market Diffusion

3.1   Motivation and Model Overview

Buying decisions for passenger cars are complex. Many factors play a role, both in private and commercial purchase decisions. Based on a survey of private passenger car buyers [30], Figure 1 gives an overview of factors ranked first in private users' decision making processes. We identify vehicle size, price and safety as the most important factors in the purchase decision. The importance of the different vehicle attributes motivates to model the EV purchase decision as maximisation of utility among several vehicle alternatives. For the future market diffusion of EVs we focus on the users' utility obtained from vehicle size, price, brand, fuel consumption and fuel type, and to a certain extend engine power, emissions and acceleration. Since our focus is on the vehicles propulsion technology, we disregard safety, gear shift and four-wheel drive.

In the model proposed here, the potential utility of each technology is calculated for each user individually. Furthermore, three user groups who differ in their purchase decisions are distinguished: (1) private car buyers, (2) commercial vehicles being used in commercial vehicle fleets only and (3) company cars which are used by employees for both commercial and private purposes. For Germany each group amounts for about one third of the annual passenger car registrations [31]. We distinguish four vehicle sizes: small, medium, large and light duty vehicles. To take the importance of vehicle size in the vehicles' utility into account, we assume that every user will buy a vehicle of the same size as his current vehicle. Purchase price and fuel consumption of a vehicle are aggregated to the total cost of ownership (TCO). The fuel consumption
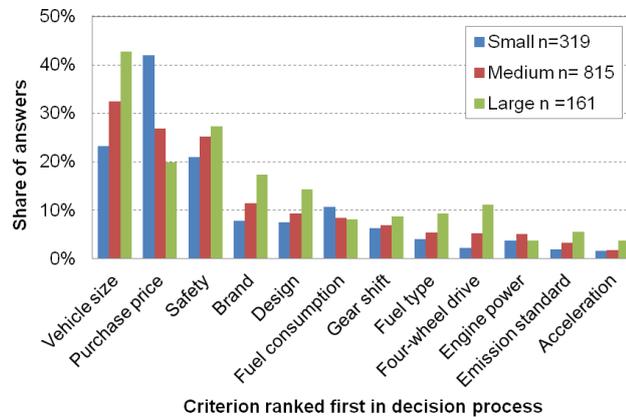
Figure 1: Criteria ranked first in the decision making process for private passenger car purchase differentiated by vehicle size. Figure is based on data from [30].

costs strongly depend on the annual VKT and the individual driving pattern, in particular the regularity of driving. For a reliable estimate, each user's driving profile is simulated as a vehicle with each of the propulsion systems (BEV, REEV, PHEV, diesel and gasoline) and the resulting fuel costs are calculated.

Fuel type, emission standards and acceleration are different for conventional internal combustion engine vehicles and electric vehicles. Furthermore, many consumers are willing to pay a price premium for a new technology [32] in general and for EVs in particular [33, 34]. The positive factors of EVs such as reduced noise, dynamic driving experience, their novelty and innovativeness are integrated in the model proposed here as willingness-to-pay-more (WTPM) of some users. Other factors are difficult to model and are assumed to be comparable between conventional and electric vehicles, such as design, safety and engine power.

Apart from the positive image of EVs as a new technology, EVs show certain limitations. One important factor is the need of frequent recharging caused by the limited electric range of EVs [35, 36]. To address this issue, we integrate the cost for the primary charging option into the individual buying decision. In addition to this, the choice of EVs in terms of brands and models as offered by manufacturers is still limited and likely to remain so for the next years. This will certainly restrain some users from buying an EV despite their potential benefits. We include this effect of a limited choice of brands into our EV market diffusion model by a two-step process: First, we assume users to stick to their current vehicle brand if possible. Second, if an EV would maximise the user's individual utility but is not available from his current manufacturer, then a share of users (depending on the number of brands offering EVs in that year) is assumed to choose an EV from another manufacturer and the rest of the users are assumed

to choose their second best vehicle option.

One of the most important aspects of our proposed EV market diffusion model is the usage of real-world driving profiles. This is a major improvement over existing models and has to our knowledge not been used comprehensively in an EV market diffusion model so far. Here and in the following, a driving profile comprises all trips of an individual vehicle over a fixed observation period including starting time, duration and purpose of the trip. The distribution and regularity of trip lengths varies strongly between different users and influences the TCO and potential use of EVs significantly. We analysed driving profiles of at least one week and found shorter periods to be too unreliable to draw conclusions on the potential use of an individual vehicle as EV (cf. figure 5 below and [37]). Based on the individual driving profile, each vehicle is simulated as gasoline and diesel vehicle and as BEV, PHEV and REEV. The resulting electric driving share as PHEV or REEV and the annual VKT are used to calculate the individual TCO of each driving profile and vehicle option.

Based on the individual TCO and the additional positive and negative factors integrated in the model as user specific utility, the utility maximising propulsion technology for each driving profile is chosen. Thus, in each user group, a share of driving profiles will correspond to EVs. This share is then extrapolated to the annual registrations of vehicles in this user group. The model outputs are the individual utility of each vehicle technology and the individual purchase decision in a given year. The technological and economical parameters vary over time and the decision process is repeated for each year. The annual registrations are built up to a stock of EVs via a stock model.

To summarise, the model is structured as in figure 2. There are three main model steps, (1) the EV simulation, (2) the utility calculation and (3) the stock model. Within these steps there are certain parts where actual user behaviour is integrated. We base the EV simulation on driving profiles in an infrastructure scenario. Furthermore, the cost for infrastructure, the WTPM and the brand loyalty of each individual user are incorporated into the utility calculation. While the first two model steps are done individually for every vehicle driving profile, the stock model aggregates the preceding results to a market diffusion. The data used for modelling, in particular the driving profiles and the WTPM, will be discussed in more detail in the following section. The different steps of the model will be explained in more detail in section 3.3.

3.2   Data: Driving Profiles, Willingness-to-pay-more, and Techno-economical Parameters

Driving profiles

The whole model is based on driving profiles which are analysed in the EV simulation. Here and in the following, a driving profile is defined as all trips of an individual vehicle including the departure and arrival time as well as the
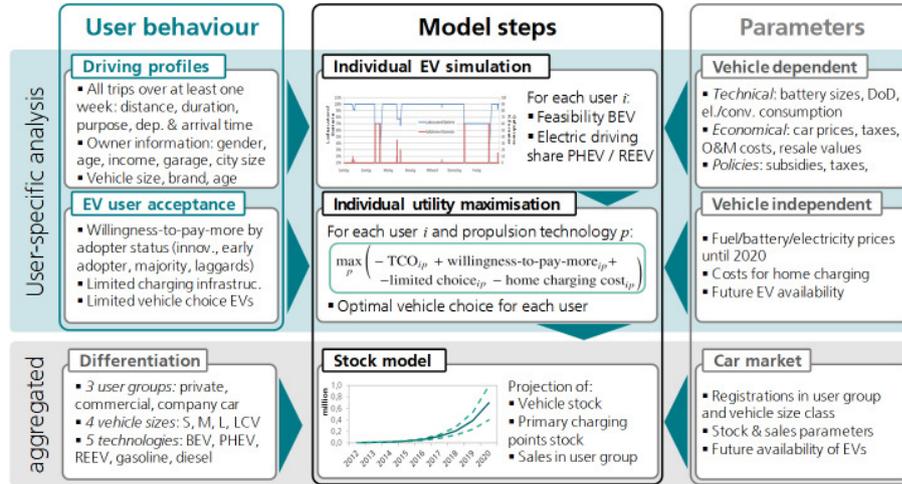
Figure 2: Overview of the proposed model for the market diffusion of electric vehicles using real-world driving data. Based on individual driving data from private, commercial and company cars (left panel) and using techno-economical parameters (right panel), the market shares of different propulsion technologies are determined in three steps (central panel): (1) each driving profile is simulated as EV and conventional vehicle; (2) based on the TCO, the cost for home charging, the limited choice of EV makes and models and the individual willingness-to-pay-more the utility maximising vehicle option is chosen for each driving profile; (3) the vehicle choices are extrapolated to market shares and aggregated to a vehicle stock.

distance travelled together with information about the purpose of the trip (to work, to home, leisure, shopping, other) and additional information on the vehicle (size, brand, age, annual VKT) and its owner. For private car owners and company cars, we use the German Mobility Panel [38] which has already been used for EV analyses (see e.g. [28, 39, 40]). For commercial users we use the REM2030 Driving Profiles collected by the authors with GPS trackers [41]. Both data sets are described in detail in [28, 42] and are publicly available. We use these datasets as they cover observations of at least one week, which is crucial for reliable estimates of a vehicle driving behaviour, in particular for EVs (see [28, 43, 44] and section 4.3). The additional information for the private driving profiles (including company cars) contains also socio-economic data about the car owner (age, education, sex, income, city size of residence, typical over-night parking spot, household size). Similarly, the commercial driving data contains additional information about the company (no. of employees, city size of head quarter location, total number of vehicles in fleet).

EV user?	EV interest?	purchase intention?	group label
yes	-	-	innovators
no	yes	yes	early adopters
no	yes	no	majority
no	no	no	laggards

Table 1: Definition of private adopter groups according to [49]. Participants in survey answered the indicated questions and were considered members of the four indicated adopter groups. A small number of respondents answered the questions as no,no,yes and have been excluded from further analysis.

Willingness-to-pay-more

An important aspect of an EV's utility are the positive non-monetary effects of these vehicles. They are perceived as new and innovative, as silent and environmentally friendly. These positive aspects of EVs are reflected in a WTPM of some users and the amgnitude of the WTPM depends on the users position in the adoption process [32, 45]. Of course, a stated willingness-to-pay is not equal to the actual willingness-to-pay in a buying decision [46, 47]. However, the stated WTPM gives an indication for the appreciation of a new technology and an approximation of the actual WTPM. Using a WTPM is a common approach in market diffusion models for electric vehicles [48, 20].

To assess a private user's position in the adoption process of EVs and their individual WTPM, we use large empirical data sets (see [33, 34, 49], cf. [50, 51, 52]). Here the WTPM has been determined independently for four adopter groups with a different attraction to electric vehicles: (1) users of electric vehicles, identified as likely innovators, (2) attracted individuals with purchase intention in the near future, identified as likely early adopters, (3) attracted individuals without purchase intention, identified as likely early and late majority, (4) uninterested individuals, identified as likely laggards (cf. table 1). The four adopter groups were formed by the participants' answers concerning their current vehicle usage, the interest in EVs, and intention to buy an EV in the near future (see [49, 53, 54] for details). Our aim is to combine these survey results with the driving profiles and to assign each driving profile to one of the four adopter groups with their WTPM.

Members of the four adopter groups differ significantly in socio-economic variables like household income, employment status, household size, city size and the willingness to accept a higher price for an electric vehicle [33, 34, 49, 53]). As the data set also contains information about age, sex and education of the user groups, we are able to assign each driving profile to one of the four groups according to their resemblance with the other group members (see section 3.3.2 for details and 4.5 for a validation of this assignment). The participants stated an individual WTPM for EVs. We will use the adopter group average WTPM to include the positive aspects of EVs mentioned earlier. The percentage WTPM

user group	share of users	willingness-to-pay-more
innovators	0.5%	30%
early adopters	1.5%	15%
majority	48%	10%
laggards	50%	1%

Table 2: Groups of private users and their willingness to pay more (WTPM). The numerical values for the WTPM are median values of the group members' answers.

is converted to absolute monetary values by using the conventional reference vehicle in that vehicle size (Gasoline for small and medium-sized vehicle, Diesel for large and light duty vehicle (LDV)). For the individual user, the positive aspects are finally included in the utility calculation by subtracting the absolute WTPM from the vehicle list price (LP_i in eq. (3) below). The specific values are summarised in table 2.

Although the described data set contains about 1,000 respondents, it is not representative for the group sizes in Germany [33, 34], i.e. users of EVs and other EV friendly groups are clearly overrepresented. This is useful for the validity of the average WTPM in the groups. To correct the non-representative group sizes, we use a second survey representative for private German car buyers [55, 56]. The groups are defined in the same way, i.e. according to EV ownership, interest in EVs and purchase intention. Since the latter survey is representative, we use it to determine the relative size of the adopter groups. The resulting share of each adopter group is summarised in table 2.

Techno-economical Parameters

The different modelling steps require assumptions for techno-economical parameters concerning the vehicles (retail prices, specific fuel consumptions, battery sizes and depth-of-discharges (DoD)) as well as the car market (annual sales per segment (small, medium, large, LDV) and user group (private, commercial, company car) and age-dependent scrapping probabilities) and framework conditions (fuel, electricity and battery prices). Since the purpose of the present paper is to introduce and discuss our model, the individual techno-economical parameters are needed. However, for later use in section 4.3, we summarise the assumed battery sizes, DoDs and energy consumptions of the vehicle types considering here in table 3. The battery sizes and DoDs have been developed in cooperation with the major German car manufacturers [57, 31] and the fuel consumptions are based on [58].

3.3   Formal Description of the Model

Following the informal description of our model and the data used in the previous sections, we will now discuss the formal modelling steps in more detail. Some of

	BEV		REEV		PHEV	
Battery size C in kWh and Depth of Discharge (DoD)						
	C	DoD	C	DoD	C	DoD
Small	20	90 %	13	80 %	7	75 %
Medium	24	90 %	16	80 %	10	75 %
Large	28	90 %	19	80 %	13	75 %
LDV	32	90 %	22	80 %	16	75 %
Consumption c_e in kWh/100km and c_c in litres/100km						
	c_e	c_c	c_e	c_c	c_e	c_c
Small	19.1	-	19.1	6.6	17.8	5.6
Medium	23.3	-	23.3	8.2	22.0	7.0
Large	25.1	-	25.1	10.4	23.8	8.9
LDV	37.6	-	37.6	12.8	35.0	11.0

Table 3: Technical parameters for the battery simulation. Battery capacities C in kWh, electricity consumption c_e in kWh/100km and fuel consumption c_c in litres/100km. The sources and assumptions for these parameter values are described and discussed in [57].

the model steps (the EV simulation and TCO calculation) have been published already [28, 33, 34, 59, 60] but the other parts and the combination to an EV market diffusion model are new. The first step of the model is simulate each vehicle with its individual driving profile as EV. Based on this vehicle simulation, the utility for each user of their vehicle with each propulsion technology is calculated individually. Finally, the individual utility-maximizing decisions are aggregated to vehicle sales in a stock model.

3.3.1 EV simulation

With the driving profiles described above we simulate the state of charge (SOC) of a battery for a specific point in time t for each user as

$$\text{SOC}(t + \Delta t) = \begin{cases} \text{SOC}(t) - d_{\Delta t} \cdot c_e & \\ \min\{\text{SOC}(t) + \Delta t \cdot P_{loc_t}, C \cdot \text{DoD}\} & \end{cases} \text{for} \quad \begin{matrix} d_{\Delta t} > 0 \\ d_{\Delta t} = 0. \end{matrix} \quad (1)$$

where the battery with capacity C and depth of discharge DoD is initially fully charged $\text{SOC}(0) = C \cdot \text{DoD}$. Here $\text{SOC}(t)$ denotes the state of charge at time t. The distance driven between t and $t + \Delta t$ is given by $d_{\Delta t}$. The consumption of electricity in kWh/km depends on the car size and is denoted as c_e. Furthermore, P_{loc_t} in kW describes the power for charging at the location where the car was parked at t. If no charging infrastructure is available, $P_{loc_t} = 0$. Note that different battery capacities are used in the simulation for different vehicle sizes and EV types (cf. Table 3). If the car is driven ($d_{\Delta t} > 0$), the battery is discharged by the energy needed for driving the distance $d_{\Delta t}$. Otherwise ($d_{\Delta t} = 0$), it is charged with the power P_{loc_t} for the time Δt if necessary and

charging infrastructure is available ($P_{loc_t} > 0$). In the simulation, no fixed step width Δt is used, but the result of each individual trip with its trip duration Δt or the parking duration Δt are used.

We analyse each driving profile by simulating a battery profile by Eq. (1) to estimate the technical EV potential. This technical EV potential delineates whether a BEV would be able to cover the whole driving profile with a fixed battery size or, in the case of a hybrid vehicle (REEV, PHEV), what electric driving share s_i user i would achieve (cf. [28] for details and section 4.3 for results). Furthermore, a simulated $\mathrm{SOC} < 0$ for a BEV indicates that at least one trip (or one chain of trips without charging infrastructure at intermediate parking spots) of the simulated driving profile was longer than the electric driving range of the BEV. The latter means that the particular driving profile cannot be driven with a BEV. All technical parameters for the EV battery simulation which will be used in section 4, are given in Table 3.

As mentioned before, EVs are charged when charging infrastructure is available at a parking position. The driving profiles contain information on the purposes of the trips but not their exact location. Hence, we also have to define scenarios for charging infrastructure (see [28, 42] for details on charging infrastructure scenarios). In the following, we assume: (1) PHEVs and REEVs drive electrically until the energy in the battery is used up completely before the conventional propulsion is used; (2) Private and company car owners charge their vehicles with a power of 3.7 kW whenever they are at home; (3) Commercial vehicles are only charged overnight with 3.7 kW no matter where they are parked.

To summarise, the battery simulation is performed for each vehicle as each EV option for each year. The results are the electric driving shares as PHEV and REEV and the substitutability by BEV for each individual vehicle i.

3.3.2 Total cost of Ownership and Utility Calculation

In a second step the economic potential and utility is determined for each driving profile. We calculate each user's total cost of ownership (TCO) for different propulsion systems. The annual total cost of ownership TCO_a consists of capital expenditure a^{capex} and operating expenditure a^{opex}

$$\mathrm{TCO}_a = a^{\mathsf{capex}} + a^{\mathsf{opex}}. \tag{2}$$

We use the discounted cash-flow method with resale values and calculate the investment annuity for user i as

$$a_i^{\mathsf{capex}} = p\,\frac{\mathrm{LP}_i \cdot (1+p)^{T_1} - \mathrm{SP}_i}{(1+p)^{T_1} - 1} + I_{\mathrm{CI}_i} \cdot \frac{p\,(1+p)^{T_2}}{(1+p)^{T_2} - 1}. \tag{3}$$

The list price LP_i (for vehicle and battery) is multiplied by the annuity factor consisting of the interest rate p and the investment horizon T_1. SP_i denotes

the sale price of vehicle i for resale after T_1 years and depends on the vehicle's annual vehicle kilometres travelled (VKT). The resale value is calculated for each user i with his individual annual VKT_i. We use results of [61] with $\mathrm{SP}_i = \exp\left[\alpha + 12 \cdot \beta_1 T_1 + \beta_2 \mathrm{VKT}_i/12\right] \cdot \mathrm{LP}_i^{\beta_3}$ where the parameters $\alpha = 0.97948$, $\beta_1 = -1.437 \cdot 10^{-2}$, $\beta_2 = -1.17 \cdot 10^{-4}$ and $\beta_3 = 0.91569$ have been obtained by regression (see [61] for details) and T_1 denotes the vehicle's age in years at the time of resale.[1] We use different values for T_1 for private and commercial users reflecting the different average vehicle holding times. The second term describes the investment for the user-specific charging infrastructure I_{CI_i} multiplied by the annuity factor without residual values and its specific investment horizon $T_2 = 15$ years.

The operating expenditure of user i for one of the propulsion technologies is calculated as

$$a_i^{\mathsf{opex}} \;=\; \mathrm{VKT}_i \,\cdot\, \left(s_i\, c_e k_e \;+\; (1-s_i)\, c_c k_c \;+\; k_{\mathsf{OM}} \right) \;+\; k_{\mathsf{tax}} \;+\; k_{\mathsf{CI}_i}. \quad (4)$$

We multiply the vehicle kilometres travelled per year by user i (VKT_i) with the cost for driving in electric mode plus the cost for driving in conventional mode and the cost for operations and maintenance (k_{OM}). The cost for electric driving consists of the electric driving share s_i, the electric consumption c_e in kWh/km and the cost for electricity k_e in EUR/kWh. The same holds for the conventional driving where the share of conventional driving $(1-s_i)$ is multiplied by the conventional consumption c_c in litres/km and the cost for conventional fuel k_c in EUR/litre. Finally the annual vehicle taxes k_{tax} in EUR/yr and the annual operating cost for charging infrastructure k_{CI_i} (in EUR/yr) are added. By adding the infrastructure cost to the TCO calculation, we address the fact that users must have at least one charging point to charge their vehicle regularly. For private car users, we distinguish users that have a garage attached to their homes or leave their car on the street overnight [62].

To assign each driving profile to one of the adopter groups with their WTPM we used the following algorithm. For each driving profile, we first calculate the agreement in socio-demographic characteristics with each survey respondent. Matches were collected from seven variables: sex, age, employment status, education, house hold size, household income and city size (all variables were categorical). That is, a driving profile could achieve up to seven matches with each of the survey respondents from a known adopter group. The number of matches $m_{ijk} \leq 7$ of user i with adopter group member $j = 1, \dots, L_k$ (out of the $k = 1, \dots, 4$ groups) were collected and normalised $M_{ik} = \sum_j m_{ijk}/(7L_k)$.

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[1]Please note that the regression results for the EV resale values imply a higher absolute resale price SP but lower relative or percentage resale value $\mathrm{RV} \equiv \mathrm{SP}/\mathrm{LP}$ when compared to internal combustion engine vehicles (ICEs). If we assume the vehicle's age and annual VKT fixed at average values, the sales price is given as $\mathrm{SP} = c \cdot \mathrm{LP}^{\beta_3}$ with some constant c. Thus the relative resale value will be given as $\mathrm{RV} \equiv \mathrm{SP}/\mathrm{LP} = c \cdot \mathrm{LP}^{\beta_3 - 1}$ and accordingly $\frac{\mathrm{RV}_{\mathsf{EV}}}{\mathrm{RV}_{\mathsf{ICE}}} = \left(\frac{\mathrm{LP}_{\mathsf{ICE}}}{\mathrm{LP}_{\mathsf{EV}}}\right)^{1-\beta_3} < 1$ since $\mathrm{LP}_{\mathsf{ICE}} < \mathrm{LP}_{\mathsf{EV}}$ and $0 < \beta_3 < 1$.

The driving profile i should then be assigned to group k where the overlap was the largest $M_{ik} > M_{il} \forall l \neq k$. However, since the relative group size should be limited (the number of innovators is rather small), we took only the top 0.5% (cf. table 2), i.e. those 0.5% with the largest overlap with the survey innovators, as innovators. The other potential innovators were then assigned to their second best matching adopter group. The same procedure was applied to the following groups in descending order in the innovation process: innovators, early adopters, majority and laggards (see [57, p. 182] for computational details). As a result of this algorithm, each driving profile has been positioned in the adoption process according to its socio-demographic variables with an associated WTPM. The validity of this assignment is analysed in section 4.5 below.

To assess the WTPM of commercial vehicle fleets, we used the results from a survey of approximately 500 German fleet managers [63]. About half the fleet managers stated a WTPM with an average of 10%. Again, this WTPM needs to be assigned to individual commercial vehicle driving profiles. We used company size (measured as number of employees) as a proxy for the position in the adoption process. Since larger companies seem more likely to engage early in innovative technologies, commercial vehicles from companies with more than 250 employees were assigned a WTPM of 10%. About 50% of the driving profiles are from such a company in agreement with the results from [63]. No reliable data was available for WTPM of company car buyers. We assume that company car buyers have zero WTPM and use this in the model.

Since EVs are in an early market phase, the choice of models and brands is and will remain limited for the next years. This fact slows down the market diffusion of EVs since brand and design are vehicle purchase criteria (cf. Figure 1). The limited choice of brands and models is included in the EV market diffusion model proposed here. In a first step the present and near-future choice of EVs were collected (from press announcements). Announcements for up to two years in the future were available. Based on this data and the relevant number of brands within each vehicle segment for normalisation, a logistic regression of the upcoming brands was performed. The resulting logistic availability function has been extrapolated into the future. This availability function is integrated into the purchase decision as follows: If an EV is TCO optimal for a driver of brand b and this brand has announced a vehicle for the year under consideration (or earlier) the EV will be bought by that user. If the user's brand b does not offer an EV, then some of the users choose an EV from a different brand (according to the logistic availability function) and the rest chooses the second best TCO option.

Finally, we combine all factors to the utility of the different vehicle options. We calculate the utility for each user i for each propulsion technology p and assume that each user buys the option that maximises his or her individual utility, i.e.

$$\max_{p} \left(-\text{TCO}_{ip} + \text{WTPM}_{ip} - \text{limited choice}_{ip} \right) \qquad (5)$$

where the users individual TCO_{ip} includes the cost for the home charging option or base charging point for commercial vehicles, cf. Eq.(3). Calculating the utility maximal propulsion system for each user, summing up all drivers for whom this would be an electric vehicle and dividing it by the total number of driving profiles, we obtain the shares p_l of potential EV users in the sample.

3.3.3 Aggregation and Market Diffusion

The EV simulation and utility calculation above are performed for every driving profile. We distinguish three different user groups (private, commercial fleet, company car) and four vehicle sizes (small, medium, large and LDV) where LDV are almost exclusively purchased by commercial fleets and accordingly neglected for the other user groups. We thus arrive at $3 \cdot 3 + 1 = 10$ vehicle groups l. The share of driving profiles in year t, $p_l(t)$, that are assumed to buy an EV according to their individual utility is now multiplied with the number of vehicles in the corresponding user group and vehicle size n_l. As parameters change over the years t we may calculate the EV registrations $N_l(t)$ as $N_l(t) = p_l(t) \cdot n_l$. However, vehicles that were purchased in a given year do not remain in stock forever. Instead vehicles will be scrapped with an age-dependent probability $P_{\mathsf{scrapping}}(t)$. This can also be written with a survival probability $L(t) = 1 - \int_0^t P_{\mathsf{scrapping}}(t')\mathrm{d}t'$ for a vehicle to survive until age t. With this distribution at hand, one can write the stock of EVs in vehicle group l and year t, $S_l(t)$, as the sum of EVs purchased in earlier years $N_l(t')$ that survived until year t:

$$S_l(t) = \sum_{t'=t_0}^{t} N_l(t')L(t - t'). \tag{6}$$

The survival probability has been obtained from the official German statistics (see [59] for details). A lifetime distribution for the vehicles to remain in stock is needed for the stock model introduced above. We use data for the complete German vehicle fleet and the age dependent scrapping probability over ten years. These probabilities have been calculated considering the age structure of the German vehicle stock since 2001 by computing the change between adjacent ages in subsequent years for all years available. The Weibull distribution for the survivor function is given by $L(t) = \mathrm{e}^{-(t/\tau)^{\beta}}$ where the parameters $\tau = 14.7$ for scale and $\beta = 3.5$ for shape have been obtained from a least square fit. These imply an average age for scrapping of 13.8 years and an average age of the vehicles in stock of 7.3 years, both in good agreement with other studies of the German passenger car stock [57]. This distribution will be used for the stock model of the German vehicle fleet.

3.4   Discussion

We now turn to a discussion of the EV market diffusion model described in the previous section. The distinctive features of the present model are the

individual utility maximisation based on a detailed analysis of many individual driving profiles as well as in the inclusion of commercial vehicles and company cars. The user specific analysis allows to cover a wide range of usage scenarios and to study specific user groups such as commercial drivers or potential early adopters.

The individual EV simulation is probably more abstract or mathematical than the purchase decision of private users. But it covers the important aspect of the regularity of an individual users' driving behaviour. Users are aware of EVs limited electric range and understand the general economics of low operating costs for electric driving. Similarly, the TCO calculation of Eq. (2) is rather complex but the purchase and operation costs of a vehicle are an important aspect in the purchase decision both for private [30] and commercial buyers [63]. This is indicated by the average annual VKT for diesel vehicles (22,300 km) and gasoline vehicles (11,800 km) in Germany [64] – reflecting the average fuel economy under the German conditions of both propulsion technologies. Accordingly, TCO calculations are a part of many EV market diffusion models [65, 31, 59, 66, 48, 67]. Along the same direction, recent studies pointed out that the costs of EVs are a major influence in the purchase decision [68, 33, 34, 52].

Although the TCO are an important factor in the vehicle buying decision, they alone cannot explain purchase decisions of car users, neither for private nor commercial car purchases. Furthermore, private buyers of hybrid and conventional vehicles seem to lack knowledge necessary for a TCO-based decision [69]. An analysis of the potential early adopters of EVs in Germany shows that more criteria than only the vehicle's TCO are important [33, 34, 54]. Accordingly, our model covers further important aspects of the purchase decision: (1) The need of frequent recharging was addressed in the model by adding the cost for a home charging option to the vehicle's TCO; (2) the WTPM of some user groups has been derived from surveys and is added to the driving profiles based on the vehicle owner's socio-demographic characteristics; (3) the limited choice of brands and models is included according to the current share of brands offering EVs. Overall, we attempt to make the most important factors in the EV buying decision explicit and measurable. They have been included in our model in an empirical way that allows updates or corrections when more data on WTPM or choice of models become available in the future.

The model proposed here has some advantages. It is user specific since individual driving profiles are used and the TCO and utility of EVs are calculated for each individual driver. This allows us to study a wide range of usage patterns and economical conditions as opposed to simple models based on average driving behaviour. Thus, even niche markets can be analysed (as, e.g., in [70, 54]). Furthermore, the large number of driving profiles allows the modeller to use statistical methods to assess the statistical quality of the model results (cf. section 4.2 and 4.3 for examples). Additionally, EV specific purchase decision factors such as the limited electric range and the need for a base charging spot

are addressed by the model proposed here.

One of the main disadvantages of the model are the data requirements. For reliable estimates several hundred driving profiles per user group (private, commercial, company car) are needed. These driving profiles should extend in time over at least one week (see section 4.3 below) and contain additional socio-demographic information on the car owner. Quite often, such data is unavailable and the collection of data and the connection of the different data sources requires real effort. However, driving data with limited observation time is available for many industrialised countries and the interest in EVs has triggered driving data collections over long time spans [43, 44].

The choice of model for EV market penetration depends on the specific research question asked and the accuracy required. In the present case, the model proposed here offers a detailed analysis of both private and commercial user groups, covers the vast heterogeneity of vehicle usage patterns and takes into account both the most important purchase decision criteria as well as the peculiarities of EVs. This detailed picture requires noteworthy data input. Thus, the model proposed here should give reliable and detailed results on the future market penetration of EVs if sufficiently good data are available and correctly combined.

4   Results and Validation

The present section is devoted to a validation and first results of the proposed model using individual driving behaviour. The results will focus on the special opportunities when using many driving profiles: an analysis of the statistical significance of the predicted market shares and a statistical analysis of future electric driving shares of PHEVs. Results of our model on EV market diffusion and an assessment of of market diffusion policies are given in [15].

4.1   Reproduction of Diesel Market Shares

As a proof of principle, we first show that our TCO based approach for a vehicle purchase is able to reproduce the current market shares of diesel passenger cars in German commercial fleets. This supports our general proposal of including TCO as one important factor in the purchase decision for passenger cars. We acknowledge the fact that commercial fleets are only one of the three user groups under consideration here. However, it is responsible for about one third of the annual registrations of passenger cars in Germany and thus an important market.

We study a large sample of German commercial passenger cars collected in 2002 [71]. For each vehicle in the database that has been used on the day of the survey, the lengths of all daily trips are summed up and multiplied by the average number of working days in Germany (which is 220 days per year) to

obtain an estimate for the vehicles annual VKT. In this case, the latter was not part of the survey and thus had to be calculated. For each vehicle, the TCO as gasoline and diesel car was calculated and the vehicle has been assigned the fuel type with lower TCO. For the validation purpose, we studied only medium-sized vehicles and assumed a purchase price of 19,560 Euro for gasoline and 21,560 Euro for the diesel vehicle. The average fuel prices in 2002 have been taken from [59]. The parameters for the 2002 passenger car assumptions in German commercial fleets are summarised in table 4. The estimated share of diesel vehicles in the different commercial branches are shown in Figure 3 together with the actual market share as stated in the corresponding survey.

Parameter	Unit	Gasoline	Diesel
Purchase price	Euro	19,560	21,560
Fuel consumption	l/100km	7,6	6
Fuel price	Euro/l	1.34	1.26
Operation & Maintenance	Euro/km	0.025	0.023
Insurance	Euro/a	114	242

Table 4: Overview of techno-economical parameters for TCO-based estimate of Diesel market shares in Germany's 2002 commercial passenger car fleet. Prices are without VAT.

Figure 3 shows that the estimated and actual market shares of commercial diesel passenger cars in Germany are 40–60%. In Figure 3 the commercial sectors are sorted by sample size which roughly follows the registrations of passenger cars in these segments. In most cases, the estimated market shares are very close to the actual market shares with significant deviations in the sectors HJ (transport and telecommunications), A (agriculture and forestry), and K (finance). Even if the share of diesel in a sector is well reproduced, one could still question whether the individual vehicle assignments are correct. In total, we found 54.2% of the individual assignments to be correct with a lowest success rate of 38% in branch of industry K (finance) and the highest rate of 66% in branch B (mining). Thus we conclude that a TCO based model is in principle able to reproduce the market shares of diesel passenger cars of German commercial vehicles. TCO is thus one important aspect of the purchase decision and accordingly part of many market diffusion models for EVs.

4.2   Statistical Precision of Market Share Estimates

The use of real world users with their individual driving profile allows estimates of the statistical accuracy of the market share calculations. The market shares depend, of course, on the assumptions for the decision making of the individual as well as the assumptions for fuel and vehicle prices and vehicle configurations. However, the model proposed here allows for a direct calculation of the uncertainty from a finite sample size. Note that this is not possible when aggregated
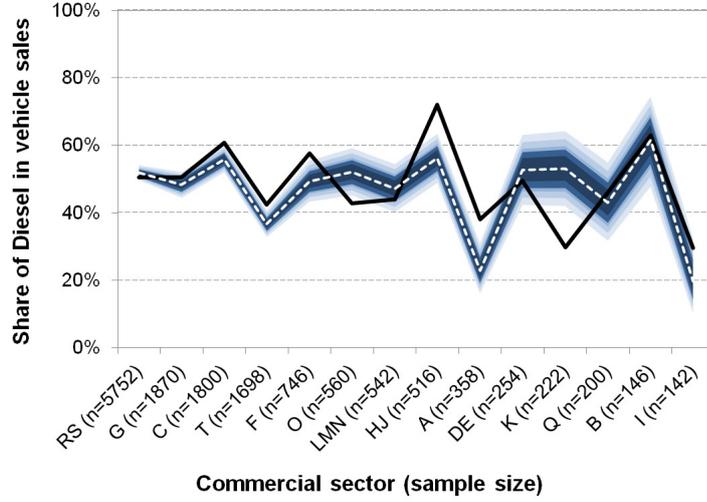
Figure 3: Diesel market shares within different branches of industry in Germany. Shown are the actual values from a large-scale survey (solid line) and the estimate from a simple TCO calculation (dashed line) together with confidence bands (in blue - see section 4.2) from the finite sample sizes (given in parentheses). See text for details of the calculation.

top-down market diffusion models, such as Bass or Gompertz [17], are used.

The effect of finite sample size can be expressed statistically as a confidence interval [72]. That is, under the assumption of a representative sample, one can compute intervals that have a high likelihood to contain the real market share. This uncertainty stemming from finite sample size can then be passed on to a result deriving from the market share, e.g. the stock of EVs or their total energy consumption, by standard error propagation techniques. More precisely, one estimates the sales share p_l of vehicle type l (e.g. propulsion technology or vehicle size or a combination of such distinctive characteristics) from the number of driving profiles k_l that fulfil the required condition (e.g. that should be EVs) and the sub sample size n_l as $\hat{p}_l = k_l/n_l$. Here, the hat ˆ indicates an estimate for the "real" market share p_l. Given a confidence level $0 < \alpha < 1$, the confidence band "contains the real value of p_l in $(1 - \alpha) \cdot 100\%$ of all cases in which confidence intervals are estimated" [72]. For a given confidence level α an upper value p_l^+ and a lower value p_l^- are calculated, such that $\hat{p}_l \in [p_l^-, p_l^+]$ in $(1 - \alpha) \cdot 100\%$ of the cases. In the present situation of market shares, one has to calculate a confidence interval for the success probability p_l of a binomial distribution $B(k_l|p_l, n_l) = \binom{n_l}{k_l} p^{k_l}(1 - p)^{n_l - k_l}$. The calculation of confidence intervals via a Gaussian distribution is a common approximation for this case. However, it is not reliable here since market shares of electric vehicles tend to be rather small, i.e. $k_l \ll n_l$, and the Gaussian approximation tends to underestimate confidence intervals in that case [73]. Using a conservative

approach, often referred to as "exact", the upper and lower confidence interval boundaries are given by [73]

$$
\begin{aligned}
p_l^- &= \mathrm{Beta}^{-1}(\alpha/2, k_l, n_l - k_l + 1) \\
p_l^+ &= \mathrm{Beta}^{-1}(1 - \alpha/2, k_l + 1, n_l - k_l).
\end{aligned}
\tag{7}
$$

Here, $\mathrm{Beta}^{-1}(x; a, b)$ denotes the inverse of the cumulative Beta distribution $\mathrm{Beta}(x; a, b) = (B(a, b))^{-1} \int_0^x t^{a-1}(1-t)^{b-1}\mathrm{d}t$ with the Beta function $B(x, y) = \int_0^1 t^{x-1}(1 - t)^{y-1}\mathrm{d}t$ for normalisation.[2] Note that p_l^- is not defined for $k_l = 0$ and we set $p_l^- = 0$ in that case.

An example for the calculated confidence bands is shown in figure 3 for the estimates of diesel market shares in German commercial sectors. Shown are the $\alpha = 0.1, 1, 5, 10, 30$ % confidence bands (from light blue to dark blue), i.e. the "true" value should lie within the confidence band in 99.9, 99, 95, 90, 70 % of the cases where confidence bands are estimated. As expected, the width of the confidence bands increases with decreasing sample size (shown in parentheses in the abscissa). In most cases the observed market share is within or close to the range of the confidence bands. Thus, the TCO calculation seems to capture important aspects of the purchase decision. Furthermore, the calculated confidence bands help to distinguish purely statistical uncertainty from possible systematic inaccuracies.

The statistical uncertainty can easily be propagated to derived quantities. Let us assume the interval to be symmetric around $\hat{p}_i$ and denote the half width of the interval by $\Delta p_l = (p_l^+ - p_l^-)/2$. The resulting uncertainty due to finite sample size of the derived result is then calculated by error propagation. Let $y = f(x_1, \ldots, x_n)$ denote a function of the input parameters x_i being uncorrelated and each having variance $(\Delta x_i)^2$. The variance of the resulting function is then given by $(\Delta f)^2 = \sum_i (\partial f / \partial x_i)^2 (\Delta x_i)^2$ [74]. For example, let n_l denote the total number of vehicle registrations in segment or user group l. Thus, the variance $(\Delta N)^2$ of the total number of registrations $N = \sum_l \hat{p}_l(t) N_l(t)$ is obtained as

$$
(\Delta N)^2 = \sum_l (\Delta p_l)^2 N_l^2.
\tag{8}
$$

Similar results can be derived for the stock of EVs. Since Δp_l is a function of the confidence level α we obtain upper $N + \Delta N$ and lower boundaries $N - \Delta N$, i.e. an α-dependent confidence interval, for the registrations of EVs. If $N - \Delta N < 0$, we use zero as lower boundary for the number of registered vehicles.

To summarise, the usage of individual driving profiles and individual modelling of the purchase decision as proposed here, allows a direct calculation of the statistical uncertainty due to finite sample size. This helps to distinguish systematic from statistical errors and is not feasible within aggregated market diffusion models.

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[2]The inverse of the cumulative Beta distribution $\mathrm{Beta}^{-1}(x; a, b)$ is available in standard software, e.g. as $\mathrm{BETAINV}(x, a, b)$ in MS EXCEL.

4.3   Simulated Electric Driving Shares

The electric driving share of a potential hybrid EV is a key factor for its economics. Regular daily driving with almost complete utilisation of the vehicle's electric driving range strongly reduces the fuel consumption costs. Thus, the regularity of driving influences the user's TCO in case of a plug-in hybrid EV. To validate the model proposed here, we performed battery simulations as described in section 3.3.1.

Electric Driving Shares for Different Annual VKT

To understand the variation in daily driving patterns and to estimate the range of possible yet realistic electric driving shares a large set of driving profiles has been simulated as PHEVs. The data set comprises privately owned vehicles as well as commercially owned vehicles both for commercial use only (commercial cars) and private and commercial use (company cars). Each of these groups makes up about one third of the annual registrations in Germany [75]. The private and company car driving profiles have been retrieved from publicly available driving data from Germany [76] and consist of all trips during one week of more than 6,000 individuals (see below). The driving profiles of commercial vehicles have been collected by the authors and consist of all trips of 354 vehicles during three to four weeks and have been described in [41, 42]. All driving profiles have been simulated as PHEVs. Here, we limit our analysis to medium-sized vehicles and assumed a battery capacity of 10 kWh with a depth of discharge of 75 % and an electricity consumption of 0.22 kWh/km, resulting in an electric driving range of $L = 34.1$ km.

The simulated electric driving shares s_i (cf. Eq. (1) in section 3.3.1) are shown as a function of annual VKT in figure 4 for the three user groups (private, commercial, and company car). There are 6,339 private and company car driving profiles in total. 3,727 (58.8%) of all private driving profiles contain the annual VKT as stated by the owner. The other annual VKT have been extrapolated from the observed driving behaviour, i.e. the observed VKT of one week have been multiplied by 52 for private users if the annual VKT was not given. For commercial fleet vehicles, the annual VKT of each vehicle have been obtained by extrapolation from their individual observation period (with an average of 18.9 days).[3]

The electric driving shares in figure 4 vary strongly between different users and with for different annual VKT. In addition to the simulated individual electric driving shares a non-parametric kernel regression is shown to highlight typical electric driving shares for varying annual VKT. Shown is a Nadaraya-Watson kernel regression with Gaussian kernel over $\sqrt{N}$ nearest neighbours [72] in which N is the number of driving profiles in a given user group (medium size vehicles private $N = 3561$, commercial fleets $N = 117$, privately used company car

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[3]See [77] for a discussion of the accuracy of these estimates.

$N = 96$). Please note that all driving profiles have been simulated as PHEVs irrespective of their individual TCO. That is, only very few of the driving profiles will actually be cost-effective as PHEVs and the first adopters of PHEVs are unlikely to cover the whole range of annual VKTs [70, 54]. Furthermore, some electric shares can be exceptionally high ($> 365 \cdot L/r$ where L denotes the electric driving range and r the annual VKT) even for large annual VKT since users can recharge up to several times a day if they return home between their trips.
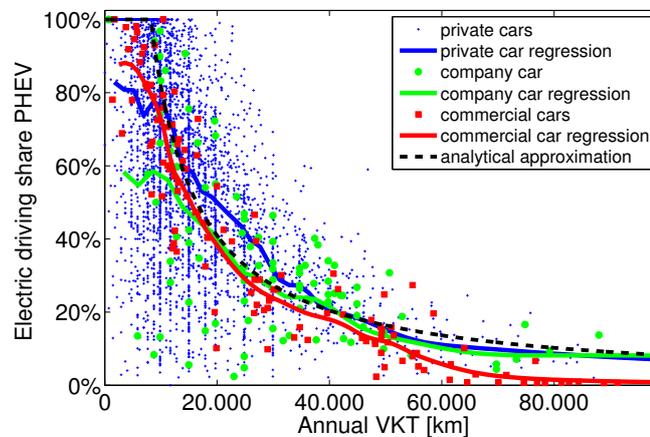

Figure 4: Simulated PHEV electric driving shares as a function of annual VKT for medium-sized vehicles. Shown are the results of battery simulations of many individual cars (symbols) and a kernel regression (solid lines): private (blue, $N = 3561$), company cars (green, $N = 117$) and commercial cars (red, $N = 96$). A simple approximation for the kernel regression given by $s(r) = 240 \cdot L/r$ (dashed black line) is also shown.

The typical electric driving share is decreasing with increasing annual VKT as expected. For given electric driving range L and annual VKT r, $s(r) = 240 \cdot L/r$ can serve as typical electric driving share s approximating the kernel regression in figure 4 between 10,000 and 60,000 km annual VKT. That is, an average user would have an electric driving share as if he was distributing his driving equally among two out of three days a year ($240 \approx 2/3 \cdot 365$). However, even for fixed annual VKT the electric driving shares within a user group vary strongly indicating large differences in the regularity of the users' driving patterns. This demonstrates that average electric driving shares are strongly misleading (even when an average is formulated as a function of annual VKT) and supports our proposed market diffusion model with individual TCOs based on the individual driving profiles.

Statistical Precision of Electric Driving Share

Since the electric driving share is an important parameter in the individual TCO calculation of PHEVs and REEVs, any estimate of it should be as precise as possible and its precision should be known. In the present section, we estimate the precision of electric driving shares when obtained from simulating multi-day driving profiles as EVs. Directly related to this, a short observation period, e.g. single-day driving profiles, can lead to strongly biased estimates of electric driving shares and the future market shares of EVs [28, 37].

We consider a user's simulated electric driving share as an average over several days T of observation $\bar{s}_i(T) \equiv (1/T) \sum_{j=1}^{T} s_{ij}$ with the electric driving share s_{ij} of user i on day $j = 1, \ldots, T$.[4] We take this as an estimate for the "real" electric driving shares as obtained from the finite sample of T days. Here, T denotes the number of observation days and not the number of driving days, i.e. a vehicle could, e.g., drive on 5 out of $T = 7$ days. Assuming the individuals electric driving share distribution to be Gaussian, the width $\Delta s_i(T)$ around user i's average electric driving share $\bar{s}_i(T)$ at confidence level α after T days is given by [72]

$$\Delta s_i(T) = t_{(1-\alpha/2, T-1)} \frac{\sigma_i(T)}{\sqrt{T}}. \tag{9}$$

Here, $\sigma_i(T)$ denotes the standard deviation of user i after T days of observation $\sigma_i(T) = [(T-1)^{-1} \sum_{n=1}^{T} (\bar{s}_i(T) - s_{in})^2]^{1/2}$ and $t_{(x,n)}$ is Student's t-distribution for n degrees of freedom [72].

As described in section 3.3, we simulated driving profiles of commercial vehicles as PHEVs. These have an observation period of up to four weeks. Following the prescription of Eq. (9) we calculated the confidence band width $\Delta s_i(T)$ as a function of observation days T for each user's electric driving share (each user's average electric driving share along with his annual VKT is shown in figure 4). Figure 5 shows the empirical cumulative distribution function (CDF) of the 95% confidence band widths Δs_i for the driving profiles being observed for different number of observation days T.

Figure 5 demonstrates how the distribution of confidence band widths is changing with increasing duration of the observation time. Note that many statistical surveys include only a single day of observation which is not able to capture the day-to-day variation individual driving behaviour usually exhibits. Furthermore, the Figure shows a clear change in the (distribution of) electric driving share precision over observation time. The 25%- and 75%-quantile as well as the median (50%-quantile) of the confidence width distributions for different observation periods T are summarised in Table 5.

The precision of the estimated median electric driving share increases quickly with growing number of observational days. However, the effect slows down

---

[4]Above we used s_i as electric driving share of user i defined as the fraction of all electrically driven kilometres and the total kilometres driven. This slightly differs this the running average over time but the difference is negligible for large T.
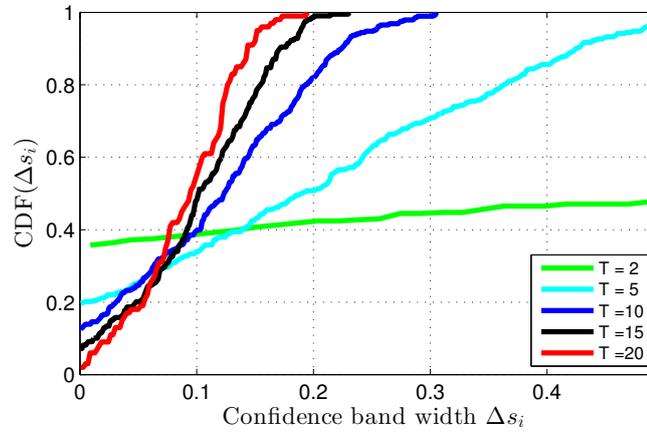
Figure 5: Empirical cumulative distribution function $\text{CDF}(\Delta s_i)$ of confidence band widths $\Delta s_i(T)$ after $T = 2$ (green), 5 (cyan), 10 (blue), 15 (black) and 20 (red) days.

period T	quantile of Δs_i		
	25 %	50 %	75 %
5 days	4.7 %	19.1 %	33.2 %
10 days	5.2 %	12.3 %	18.4 %
15 days	6.4 %	10.2 %	14.6 %
20 days	6.0 %	9.6 %	12.3 %

Table 5: Statistics of 95 %-confidence bands of simulated PHEV electric driving shares.

after about 10 days and mainly driving profiles that contain trips on a small number of days only improve noteworthy in the electric driving share precision after this period of time. But as the observation time increases, the probability of larger errors (as measured by the 75% quantile or the maximum of the CDF in Figure 5) decreases. We conclude that driving profiles should contain at least one week of driving.

The present section's results highlight the importance of simulating each individual driving profile instead of relying on assumed average electric driving shares. Furthermore, driving profiles over several days of observation time allow to estimate the statistical accuracy of the individual electric driving share and thus of the accuracy of this very specific parameter in the TCO calculation.

4.4   Future Availability of EVs in Germany

The diffusion of innovations and new technologies typically follows an S-shaped curve, well described by a logistic function [32, 17, 78, 79, 80]. We assume that the availability of EVs from different brands can be described by a logistic function, too. That is the share of brands per segment that offer an EV grows

Segment	BEV		PHEV/REEV	
	t_0	$\tau\,[10^{-3}]$	t_0	$\tau\,[10^{-3}]$
Small	2015.2	2.827	2019.2	1.292
Medium	2015.2	2.459	2014.8	1.292
Large	2024.6	3.091	2016.6	1.633
LDV	2018.3	3.153	2018.3	1.292

Table 6: Numerical parameters for the logistic function of the estimated future EV availability as obtained from regression and partially transferred between the segments.

logistically over time $A(t) = [1 + \mathrm{e}^{-(t-t_0)/\tau}]^{-1}$. Here t_0 denotes the point in time when 50% of the brands in a given segment offer an EV and τ is the time scale of change of EV availability. Technically, we collected EV announcements from different brands and calculated the cumulative number of brands per year that already offer or have announced to offer an EV in the given year (see [57, Ch. 7.4]). This cumulative number of brands has been divided by the number of brands active in that segment for normalisation. For the case of Germany, we chose all brands with non-zero new registrations in 2011 as active (26 brands in the small segment, 32 in medium and 29 in large).

The parameters of the logistic function to estimate future availability of EVs were obtained by least-squares regression and − if the amount of data is insufficient for selected segments − assumed to be partly equal between the groups. Furthermore, PHEVs and REEVs were treated as a single group since from the perspective of availability these vehicles are rather similar and many future announcements do not clearly distinguish between the two technologies. Most announcements were available for medium-sized and large vehicles. The parameters for the availability of these segment were obtained first. The τ value of medium sized vehicles has been used for small vehicles and LDVs, too. For small and large vehicles, t_0 was derived from the announced availability in 2015, i.e. for small vehicles $t_0 = \tau \ln[1/(1/26) - 1] + 2015$ and $t_0 = \tau \ln[1/(1/29) - 1] + 2016$ for large vehicles. The results of the regression for future availability of EVs from different brands in Germany are summarised in Table 6. The resulting availability functions are shown in Figure 6. The data that has been used for the least square regression is also shown in Figure 6. These are the share of brands that have announced to offer EVs in the near future for medium BEV (red squares) and medium PHEV/REEVs (blue diamonds). The agreement between the regression curve and the actual share of announcements of all active brands in the segment is good.

We observe from Figure 6 that EVs have been announced mainly for small and medium-sized vehicles. Furthermore, BEVs have mainly been announced for small vehicles and PHEV/REEVs in the medium and large vehicle segments. The obtained availability curves estimate a coverage of about 50% of the brands already for 2015 for mid-size PHEV/REEV and small BEV, somewhat later for
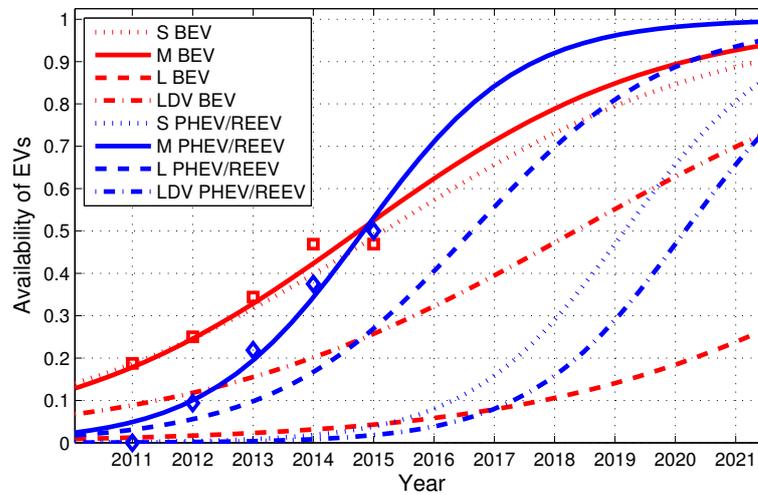
Figure 6: Projected future availability of EVs from extarpolated least square regression of model announcements from manufacturers active in the German market. PHEV and REEV announcements have been treated as one group. Also shown for medium BEV (red squares) and medium PHEV/REEVs (blue diamonds) are the share of brands that have announced to offer EVs in the near future, i.e. the data that has been used for the regression.

other segments. The expected increase in brand choice is slower only for large BEVs, about 20% of the brands are expected to offer a BEV in this segment.

4.5 Significance of User Group Assignment

We distinguish four different user groups in different stages of the adoption process: innovators, early adopters, early and late majority, and laggards [32] in order to assess each driving profile's individual WTPM in the proposed EV market diffusion model. It is important to understand the validity of this assignment and the present section aims at estimating the validity of this assignment.

In the original data set the assignment to one of the four adopter groups has been made by the respondents' answers to questions concerning their ownership of an EV, their interest in EVs and their purchase intention for an EV. These questions have not been asked in the driving profile data and the assignment was made according to the driving profile's socio-demographic variables (see section 3.3). However, in the original data set where the adopter status is known, the same assignment according to socio-demographic variables can be performed and cross checked with the actual adopter status as determined from the EV ownership, interest and purchase intention. Thus we applied the procedure described in section 3.3 to the original survey data and obtained the respondents status as determined from the similarity with other adopters. This new and the original adopter status assignment are compared in table 7.

original	new assignment				
assignment	innov.	ea. ad.	majority	laggards	*sum*
innovators	0	1	47	33	*81*
early adopters	3	3	118	125	*249*
majority	2	3	193	162	*360*
laggards	0	2	97	152	*251*
sum	*5*	*9*	*455*	*472*	*941*

Table 7: Contingency table of original and newly assigened user group for validation of the assignment. Note that the group sizes in the new assignment have been pre-determined as described in section 3.3 and table 2.

In the new assignment, 0 out of 5 innovators have been identified correctly, 3 out of 9 early adopters, 193 out of 455 from the early (and late) majority and 152 out of 472 laggards. In total, about 37% of the assignments are correct. The assignment is accordingly slightly better than an assignment by pure chance (with about 25% correct). The result is mainly determined by the two large groups of users (early/late majority and laggards). Taking only the two dominating groups $193+152 = 345$ out of $360+251 = 611$ users are assigned to their correct group, i.e. 57% $\pm$ 5.2% (at 99% confidence level, i.e. $\alpha = 0.01$) are correct and also better than pure chance (50 %). Focussing on these two large groups, table 7 can be reduced two the contingency table $(193, 162; 97, 152)$. Performing a χ^2-test of dependence, we find the old and new assignment to be significantly dependent (p-value < 0.01) as wished, both in the case of the reduced as well as the full contingency table.

To summarise, the assignment of a driving profile to a position in the adoption process (and connected to this the WTPM) is significantly better than pure chance but not very accurate. However, it seems sufficient for the modelling purposes under consideration here since the driving profile is mainly determining a user's TCO and a strong correlation between the driving behaviour (in terms of annual VKT and regularity of daily driving) and the users' WTPM is not very likely. We thus conclude that the assignment of a willingness to pay more based on a user's socio-economic characteristic is meaningful and helpful for modelling the market diffusion of electric vehicles.

5   Summary

We proposed a new approach to model market diffusion of electric vehicles in a reliable, user specific and empirical way. The model decision for different propulsion system is based on an individual total cost of ownership calculation extended by a willingness-to-pay-more for new and environmental friendly vehicles of some vehicle buyers, limited choice of EV cars available on the market and the cost for charging reflecting the current lack of public charging infrastructure and the corresponding range anxiety.

One main characteristic of the new model is the integration of differences in user behaviour, in particular annual VKT and daily driving patterns. This is important since the detailed analysis of empirical driving patterns has revealed great variations in annual VKT as well as in daily driving distances. To identify realistic electric driving shares of PHEVs and REEVs on the basis of empirical driving patterns is of relevance for the TCO calculation. Furthermore, it is needed to calculate the substitutability of conventional vehicles by BEVs. Additionally, relevant differences between the use of private, company and commercial cars can be found. In general company cars drive more on a yearly basis and often show more regular daily driving as compared to private cars. Accordingly, these user groups are differentiated in the present market diffusion model. In addition, the limited selection of EV cars is one barrier for the market penetration of EVs, despite the fact that this situation will improve in the next years. To estimate the future EV model palette a forecast on S-shaped curves has been developed.

The model quality has been tested by the forecast of market shares of diesel vehicles for commercial passenger cars. Compared to statistical data the diesel market shares calculated with the model show good agreement. The model evaluation has furthermore shown that a short observation period of one or two day could lead to strongly biased estimates of electric driving shares and therefore biased results for EVs. The quality of results increases quickly with the number of observation days. However, the effect slows down after about ten days.

In summary, we developed and tested a user specific EV market diffusion model to project future market shares of EVs and to evaluate policies stimulating EV market diffusion.

Acknowledgements

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