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Assessing the effects of a growing electric vehicle fleet using a microscopic travel demand model

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The German government seeks to increase the number of electric vehicles (EV) in the German car fleet to one million by 2020. Since some characteristics of EVs differ from conventional cars, there is an increasing need to assess the various impacts of a growing EV fleet. In this work, we have focused on possible effects related to the field of transport. We identified three important aspects and evaluated them over a period of one week using the microscopic travel demand model *mobiTopp*. First, we modelled the potential EV user groups of the near future by developing an EV user model; this model considers both interest in EVs and suitability for EV usage. Second, we simulated the travel behaviour of EV users; we used an EV usage model to consider the restrictions of EVs in choice decisions and also compared the usage behaviour of EV and conventional cars users. Third, we analysed the power consumption of the simulated EVs and evaluated the load peaks based on the simulated travel patterns. Our results indicate that a growing EV fleet implies a more heterogeneous distribution of EVs among car owners. They also indicate that the trip chain length of battery electric vehicles (BEVs) is much lower than that of extended range electric vehicles (EREVs) and conventional cars on average.

Keywords: *electric vehicles, vehicle ownership, car usage, agent based model, travel demand model*

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1 Introduction

Due to climate change and the finiteness of fossil resources, alternative fuel vehicles are receiving increasing attention and, in fact, the promotion of electric vehicles (EVs) has been placed on the political agenda in various countries. In Germany, for example, the government aims to increase the number of EVs in the German car fleet to 1 million by 2020. Since the characteristics of EVs differ from conventional cars in many ways (e.g., in driving range, local emissions, electric energy demand), there is an increasing need to assess the effects of a growing EV fleet.

Microscopic travel demand models are a promising tool to assess effects of introducing EVs on a large scale. For reliable predictions of the electric energy consumed by EVs, it is necessary to estimate the correct number of EVs and either the electric energy consumption of each EV or at least the average energy consumption per EV. The overall energy consumption depends on the type of EV as well as on the EV usage intensity. It is therefore important to allocate EVs to those car users who are likely to own an EV in the future in order to represent the EV trip characteristics correctly within the model. Moreover, EV restrictions such as limited range and high recharging times may cause adjustments in the travel patterns of EV users. Consequently, in order to gain precise model results, these adjustments also have to be considered in the simulation.

There are several studies that predict market potential of EVs (Stark et al., 2014; Ahn et al., 2008; Eggers and Eggers, 2011) or analyse the characteristics of (potential) EV buyers (Ahn et al., 2008; Eggers and Eggers, 2011; Lieven et al., 2011; Stark et al., 2014; Hackbarth and Madlener, 2013; Plötz et al., 2014); however, those results have not been integrated into travel demand models yet. Other studies analyse the impact of electric vehicles by use of travel demand models (Galus et al., 2009, 2011; Waraich et al., 2013), but these studies assign EVs only based on the distance travelled and not on sociodemographic characteristics of the owners. Knapen et al. (2012) havent integrated EVs into their model, but have assigned EVs to suitable car trip chains after the simulation. Consequently, the modelled travel behaviour is not affected. The MATSim approach (Galus et al., 2009, 2011; Waraich et al., 2013) integrates EVs into the model, but its focus is on modelling the power infrastructure and travel behaviour is only affected by the charging costs at different locations (Galus et al., 2009). None of these approaches simulates the interaction between range restrictions, EV usage and energy consumption.

The current work closes this gap by adapting the agent-based travel demand model *mobiTopp* (Mallig et al., 2013). An EV ownership model, considering the suitability of an EV based on daily travel patterns as well as peoples interest to own an EV, is used to determine whether a simulated household owns an EV or a conventional car. The models of destination choice and mode choice take range restrictions and range anxiety into account.

In this paper, we address the following questions: How can EV ownership be modelled adequately in travel demand models? How do EV owning model agents use their BEVs and EREVs? How do range limitations restrict EV owners in their car travel behaviour and how can we capture this relation in a travel demand model? What is the electrical energy demand that results from EV usage? Therefore, we have used the microscopic travel demand model *mobiTopp* to simulate the effects of three different EV market penetration scenarios over a simulation period of one week. Within the car fleet, *mobiTopp* distinguishes between conventional combustion engine vehicles (CV) and two different types of EVs: battery electric vehicles (BEVs) and extended range electric vehicles (EREVs). We have chosen Stuttgart, Germany, in the year 2025 for our study setting and have simulated travel behaviour and car usage for the greater metropolitan area.

2 Related work

Current literature describes various approaches to predict the potential of alternatively-fuelled vehicles. Many researchers base their analyses on stated preferences. For example, Ahn et al. (2008) used the stated preferences of people living in and around Seoul for a simulation analysis of changes in car ownership in South Korea. The basic condition was that all attributes are equal for all vehicle types (e.g., purchase price). They found that gasoline-powered vehicles were chosen by more than 60% of the households, whereas hybrid vehicles were chosen by 50% of the households (multiple selection was possible). This indicates that these vehicle types will retain a high future market share, at least in the near future. Eggers and Eggers (2011) found similar results for Germany. They developed a choice-based, conjoint adoption model and showed that, within the next 10 years, more than 50% of German customers would consider a hybrid vehicle, whereas only 8% would switch to a BEV or EREV. The authors conclude that the main reason appears to be the currently limited charging infrastructure (Eggers and Eggers, 2011). Based on discrete choice data, Hackbarth and Madlener (2013) found that German car buyers are currently very sceptical about BEVs. In their study, the choice probability of CVs was more than 30%, compared to only 2% for BEVs. Focusing on the predicted percentage of potential EV buyers, Lieven et al. (2011) found that only about 5% of all car buyers would choose an EV. Even though alternatively-fuelled vehicles might reach a significant market share, the market potential of BEVs will be substantially smaller than that of hybrid vehicles. Summarised, these studies indicate that, for the near future, conventional vehicles will still dominate the market.

That being said, it is difficult to predict the true potential of EVs by focussing on customer preferences alone; individual travel behaviour must be considered as well. Pearre et al. (2011) analysed longitudinal GPS data of car trips to assess the range requirements of BEVs, assuming that BEV drivers would not change their driving patterns. They found that only 9% of vehicles did not travel more than 100 miles (161 km) on any single day during the year of the study. Chlond et al. (2014) also analysed the use of private cars during one year and found that only 13% of the German private car fleet never travelled more than 100 km on any day. These findings show that only a small fraction of car holders are perfectly suited for BEV usage. An important aspect missing in these studies, however, is how EVs will be used and what effect that usage will have on the infrastructure, in particular, on electrical grids. Microscopic models are especially well suited for such analyses, due to their ability to simulate individual vehicles. Galus et al. (2009) were among the first to apply a travel demand model to analyse the usage of plug-in electric vehicles (PHEV) and their effect on electrical grids. In their work, they iteratively connected the agent-based travel simulation MATSim and the power system simulation PMPSS. Galus et al. (2011), Waraich et al. (2013), and Waraich et al. (2014) developed this approach further by integrating and evaluating different charging strategies for BEVs. In the MATSim-PMPSS approach, the energy grid is modelled as a network of interconnected energy hubs. Real electricity load curves can be used for each hub as baseline demand. As a test case, a simplified Berlin scenario for MATSim is used. In later work, a more detailed scenario of the city of Zurich is implemented. Knapen et al. (2012) used the output of the activity-based model Feathers (Bellemans et al., 2010) to predict energy demand and power peaks caused by EV-charging, considering different market shares and charging strategies. Both the MATSim-PMPSS model and the approach by Knapen et al. (2012) focus on specifying the electrical power demand caused by the usage of EVs (BEVs and PHEVs) for one day. However, neither approach explicitly considers possible changes in destination choice caused by EV limitations, such as changing destination due to limited range. However, in the MATSim-PMPSS model, agents are able to consider trip-specific costs during re-planning, in order to maximize their utility.

The *mobiTopp* model used in our study has a different focus. Although we also consider the energy aspect, our main goal is to highlight the behavioural aspect. *mobiTopp* can account for changes in destination and mode choice due to EV restrictions. Trip-specific costs cannot be considered in *mobiTopp*, since travel time and costs are fixed for all zonal relations. The study area is divided into 1,174 zones, which permits a fine-grained analysis of the electricity demand for EV charging. The spatial resolution of the MATSim-PMPSS model, in contrast, are links. MATSim models typically use a sample of 10% of the population for simulation and are only able to simulate one day. *mobiTopp* uses 100% of the population and a study period of one week. Hence, we are able to examine the daily changes in travel behaviour in more depth and track the electrical power demand for seven days.

3 The *mobiTopp* model

mobiTopp (Mallig et al., 2013) is a microscopic travel demand model that represents every person as a single entity, a so-called agent. The model has two main components: one long-term part and one short-term part. With the long-term component, conditions are determined that remain stable over a longer period. That is the population including their home and workplace locations, car ownerships and ownerships of a season ticket for public transport. The short-term part simulates the travel behaviour of the population over a period of one week. The temporal resolution of this simulation is one minute. Spatially, the study area is divided into zones. The study area used for our work, the greater Stuttgart area, consists of 1,174 zones with a total population of about 2.7 million inhabitants owning about 1.3 million private cars. Simulating the travel behaviour of the entire population for a whole week takes 28 hours on a high-end workstation.

3.1 The long-term component

The long-term component comprises a population synthesis model, a car ownership model and a public transportation season ticket ownership model.

The population synthesis model generates the population for each zone by repeated random draws with replacement of households and their associated persons from the survey data of an existing household travel survey conducted over a survey period of one week. The appropriate weighting of a households probability of being drawn accounts for the distributions of household attributes and person attributes. These weights are generated by an iterative proportional adjust-ment approach similar to that described by Mueller and Axhausen (2011). First, an initially equally distributed weight is assigned to each household. These weights are subsequently adjusted iteratively. For the household drawn, the model generates a corresponding household and every person living in this household. An activity program (a sequence of activities having three attributes: type, planned start time, and duration) is assigned to each agent based on the programs of corresponding persons in the household travel survey. The population synthesis module also assigns the workplace and school place for each person, which is done based on external matrices representing the distribution of workplaces and school places for the inhabitants of each zone. The car ownership model contains two sub-models: the car segment model and the EV ownership model. The car segment model is a multinomial logit model that uses the attributes commuting distance, gender, household size, household income, and number of household cars. We describe the EV ownership model in detail in section 4.2. A binary logit model determines season ticket ownership for public transport using the attributes employment status, gender, number of cars per household size, car availability, and district of residence.

3.2 The short-term component

The short-term component chronologically and simultaneously simulates the activity programs of all agents. This simulation contains the execution of activities and trips, as well as destination and mode choice decisions. The simulation starts on Monday at 00:00 and ends on Sunday at 23:59. Every agent starts the simulation by performing an activity. When the activity ends, agents inspect their activity programs to find the next scheduled activity. For each activity, agents make a destination and a mode choice and then start the trip to the next destination. After reaching the desired destination, agents start performing the next activity. If agents start a trip from home and use the mode car-as-driver, they select one of the households available cars. This car is then no longer available to other household members until agents return home. The agents' car selection depends on the cars available, whether agents have an assigned car for personal use and the expected trip distance. If a car for personal use is available, this car is selected. Otherwise, agents select one of the remaining cars that has sufficient range, where possible, taking one not personally assigned to someone else.

3.2.1 Destination choice
For activities with fixed locations (home, work, school), the agents use the fixed destinations assigned in the long-term component throughout the week. For activities with flexible locations, they perform a destination choice using a multinomial logit model with the three attributes attractiveness-of-destination, travel time, and travel cost. To calculate travel time and cost, the algorithm not only considers travel time and cost for reaching the next possible destination, but also the travel time and cost for travelling from the next possible destination to the next known destination of an activity with a fixed location. The model is described in more detail in Mallig et al. (2013).

3.2.2 Mode choice
The mode choice model in *mobiTopp* offers five modes: walking, cycling, public transport, car passenger, and car driver. The model only considers the main transport mode for each trip. Consequently, there is no mode change during a trip. The mode choice model is a multinomial logit model based on ten variables: time, cost per kilometre, car availability, season ticket ownership, activity type, weekday, household type, employment status, trip length, and commuting distance. The model is described in detail in Kagerbauer et al. (2015). This model seeks to realistically represent the actual available choice set. Thus, the model only allows for the full choice set when the agents are at home and a car is at their disposal. When the agents are not at home and the mode of the last trip was car driver or cycling, only the mode used for the last trip is available. When the agents are not at home and the last mode used was neither car driver nor cycling, the only modes available are walking, public transport and car.

4 Modelling electric vehicles

We faced two mayor challenges when including EVs into the *mobiTopp* framework. The first challenge was to ensure that EVs are allocated to those households and persons who are likely to own an EV in the future. We therefore developed an *EV ownership model* that assigns EVs to households and car users according to car usage data. The second challenge was to determine a realistic representation of the particular characteristics of EVs, notably, their limited range and their charging process. Therefore, we included an *EV usage model* in the *mobiTopp* framework.

4.1 Input data
Two datasets were used as input for the EV ownership model: data from a *car usage model integrating long-distance events (CUMILE)* and data on EV user characteristics from the MINI E Berlin field trial.

4.1.1 Car usage model CUMILE
The inclination of car owners to replace a conventional car with an EV depends substantially on their car usage characteristics, for example, how often per year they use the car long distance travel. Since representative, longitudinal car-usage surveys are not available for Germany, we developed *CUMILE* in order to model the car mileage for every day of a full year for a representative private car fleet (see Weiss et al. (2014); Chlond et al. (2014)). *CUMILE* is based on four German travel surveys, which are described in Table 1.

The travel surveys used reflect the travel characteristics of persons. However, we modelled the longitudinal usage characteristics of cars. The *CUMILE* car fleet consists of cars whose owners participated in the MOP-EM and the MOP-FCOR surveys. Both private cars and company cars used for combined private and business purposes were included in *CUMILE*. The survey structure also enabled us to determine which person in the household was the main user of the car, that is, which person in the household was responsible for the highest share of the cars annual mileage. The representativeness of the sample is ensured by weighting the data according to the socio-demographic characteristics of the car owner and the cars features. Information on the characteristics of long-distance trips was obtained from the long-distance travel survey INVERMO. For validation, we used results of the Mobility in Germany (MiD) 2008 survey.

Table 1. Travel surveys used as input for *CUMILE* (see Streit et al. (2015); Zumkeller et al. (2006); Zumkeller and Chlond (2009); infas and DLR (2010))

Survey Name	Type of Survey	Survey Period	Sample Used	Survey Population	Survey Waves Used
German Mobility Panel (MOP) – Every-day Mobility (EM)	Trip diary	7 days	2,438 households 3,950 car users	Population living in Germany	2005-2011
MOP- Car Mileage and Fuel Consumption (FCOR)	Car use diary	56 days	3,141 cars	German car fleet	2005-2011
INVERMO	Long distance trips	3 trips	17.000 persons 10.800 car trips	Population living in Germany	2000-2002
Mobility in Germany (MiD)	Trip diary	1 day	22,959 households 34,601 cars	Population living in Germany	2008

The *CUMILE* algorithm consists of four steps (see Figure 1). In the first step, we analysed the individual car travel data of survey participants during the MOP-EM week. Since MOP does not allocate specific cars to single trips, we developed a heuristic assignment of cars to individuals to approximate the mileage of a specific car for every day of the MOP week from the travel diaries. In the second step, we estimated the car usage for typical days of the year. The MOP participants report whether it was a rather typical or an atypical day for every survey day, that is, whether the car was under repair or the car user was ill or on holidays. Since most trips made on a typical day are frequently repeated, such as commuting trips, we assumed that every weekday was representative for the same day of the week throughout the course of one year. In the third step, we calculated the car mileage per day during the period of the MOP-FCOR survey.

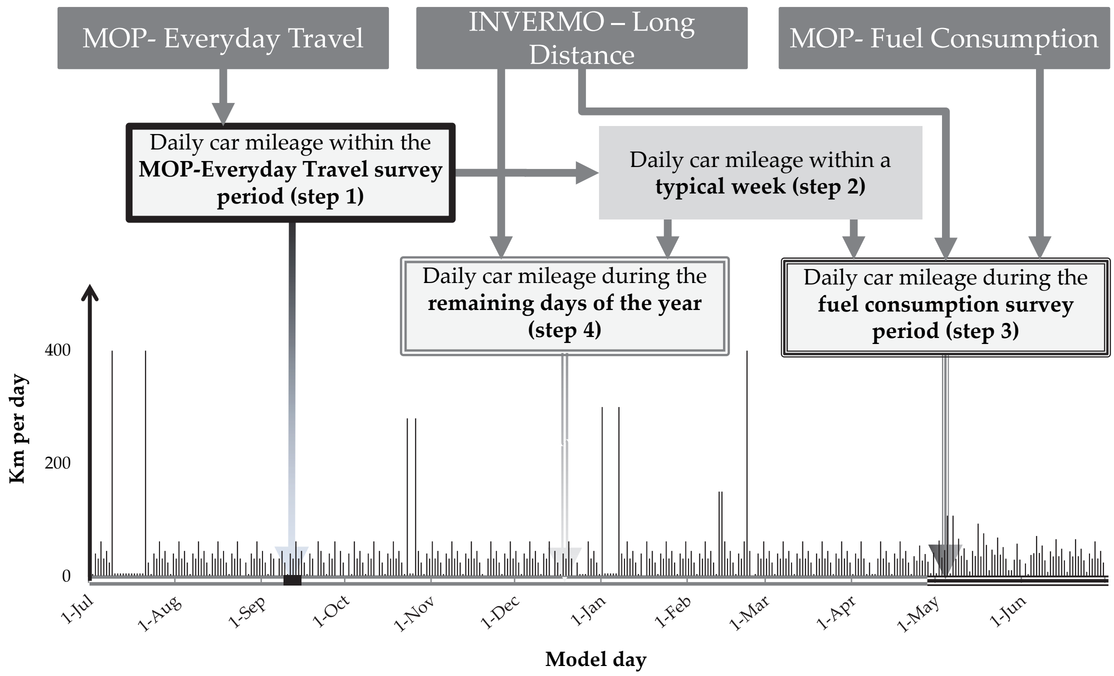

Figure 1. Structure of CUMILE *visualizing the model results for one car*

The algorithm compares the typical daily mileages calculated in the second step with the actual metered mileages between refuelling procedures. When the actual car usage was overestimated, the car mileage was set to zero on randomly selected days. When the actual car mileage was underestimated, the model assumes the car was used for an additional long-distance trip (LD-trip) and draws a feasible LD-trip from the INVERMO survey. In the fourth step, we modelled the car mileages per day for the remaining days of the year. As in step three, the algorithm detects whether the typical mileages explain the reported annual mileages. In case of an overestimated car usage, the car mileage was set to zero on randomly selected days. When the actual car mileage was underestimated, the LD-trip drawing procedure was run again. Steps three and four procedure we repeat until the daily car mileage of all days was calculated, given that the annual car mileage was correctly represented.

4.1.2 MINI E Berlin field trial

The two MINI E Berlin field trials (MINI E 1.0 Berlin and MINI E Berlin 2.0 powered by Vattenfall) were conducted in greater Berlin, Germany, between 2009 and 2011. Both field studies were set up by the BMW Group and Vattenfall Europe and funded by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety. Moreover, they were both part of a large-scale international field trial (see Vilimek et al. (2013)).

The objective of these field studies was to examine the experience and behaviour of BEV users in an ecologically valid setting. Initially, participants were recruited via an online screening instrument, which was widely advertised in both print and online media. People interested in leasing an EV at a monthly leasing rate of 400 Euros and who had the possibility to install a private charging infrastructure were asked to apply for participation in the study. Afterwards, applicants fulfilment of the participation requirements was tested in a selection and communication process. This included technical inspections of the real viability of installing charging infrastructure and the signing of a leasing contract. Hence, the study participants went through similar steps as when buying an EV. First, they became aware of the availability of an EV over the media or by word of mouth. Second, they reviewed their ability to lease an EV under the stated terms. Finally, they signed the leasing contract. The EV was a typical BEV with a range of about 160 km under normal conditions. For further details on the methodology of the field trials, see Cocron et al. (2011), Franke et al. (2012), and Buehler et al. (2014).

In total, 110 users were recruited. Based on the characteristics of the aforementioned recruitment process, we assume that this sample represents early adopters of EVs. Indeed, the socio-demographic characteristics of this sample were similar to reported findings regarding the profiles of early EV adopters (Wietschel et al., 2012). On average, participants drove 16.2 km between their home and work place (Guenther et al., 2014). The participants had a mean age of 48 years (SD = 10.00); 85% were male and 81% held a university degree. 94% of the participants were employed and only 23% reported a monthly net household income below 3,000 Euro. Every participant lived in metropolitan Berlin, Germany. The average size of the participants households was 2.8 persons (52% of households had less than three household members). The average number of cars per household was 1.8, and 43% had a middle-class car (compact cars, middle-class cars, mini vans).

4.2 The EV ownership model

One challenge was to ensure that EVs were allocated to those households and persons who are likely to own an EV in 2025. Therefore, we developed an EV ownership model to assign EVs to households and car users. For the present analysis, we assumed that two principal dimensions affect the EV ownership decision: (1) Could an EV fulfil a persons mobility needs in the same way as a conventional car? That is, is the EV owner suitable for EV ownership from the car-usage perspective? (2) Does the EV owner belong to a socio-demographic group that appears to be interested in new technologies like EVs and is inclined to own such a car? To reflect both dimensions, our EV ownership model considers EV usage suitability and EV interest in two separate parts. Combining both parts helps us to determine EV ownership in a more realistic manner, since not only early adopters are considered, but also car owners for whom EV possession is suitable from the car-usage perspective (i.e., they make only a few long-distance trips within a year). In so doing, we attempt to model a future market of EV owners beyond the early adopters.

4.2.1 Model of EV usage suitability

We modelled the probability that a *mobiTopp* agent is suitable for EV ownership Psu using a binary logit approach. We estimated the model based on the *CUMILE* (see Section 4.1.1) model output containing the driven mileage of every car for a representative car fleet for every day of one year. Based on the assumption that EV owners tend to prefer range setups that are somewhat above their actual range needs (Franke and Krems, 2013; Franke et al., 2015b), we divided the cars included in *CUMILE* into two groups: cars with a daily mileage under 90 km (exceeding this threshold on 12 or fewer days per year), and cars covering more than 90 km on more than 12 days per year. The main drivers of cars of the first group are thus defined as suitable for EV usage, whereas the main users of the cars of the second group are defined as unsuitable. We set the EV mileage threshold at 90 km, although the assumed average BEV range in *mobiTopp* is 115 km, since people desire safety buffers to keep themselves in their range comfort zone (Franke et al., 2015a) and avoid range anxiety (Rauh et al., 2015). The EV usage suitability model describes the probability that a car owner is suitable to hold an EV as a function of several socio-economic attributes. These include gender, commuting distance, spatial structure of the owners home district, number of cars in the household, employment status, and household size. The estimation results of the logit model are shown in Table 2.

For persons living in one-car households or in multiple person households, EV suitability is roughly 40% less likely than for those living in multi-car households or one-person-households. Furthermore, people with full-time employment are less likely to be suitable for an EV. The most important determinant, however, is the commuting distance: the shorter the commuting distance, the higher the likelihood (up to 7.6 times) of EV suitability.

4.2.2 Model of EV interest

A car owners EV suitability is not sufficient to determine actual ownership, since we do not know whether he is interested in new mobility concepts. To obtain a rough estimate of the car owners potential interest in EVs, we used the data on socio-demographic characteristics of the users participating in the MINI E field trial (see Section 4.1.2). We are aware that similarity in socio-demographic characteristics is not sufficient to predict usage interest. It was, however, the only available indicator possible for our research approach.

The EV interest model is based on a similarity measure. Based on socio-demographic characteristics, the model identifies *mobiTopp* agents similar to the participants of the MINI E Berlin field trial. The similarity s_{ij} of a *mobiTopp* agent i and a MINI E field trial participant j is given by the following equation:

$$s_{ij} = \frac{1}{n} * \sum_{k=1}^{n} f(z_{ik}, z_{jk}), \tag{1}$$

where $f(x,y) := \begin{cases} 1 & \text{if } x = y \\ 0 & \text{otherwise} \end{cases}$ and

n: number of socio-economic attributes
z_{xy}: socio-economic attribute

We considered six socio-economic attributes: gender, age class (six groups), employment status (yes or no), number of cars in the household, car segment (small, medium or large; see section 4.1.2) and commuting distance (seven groups; see Section 4.2.1). The distance measure d_{ij} ranges between 0 and 1; a value of 0 indicates that i and j are very similar for the attributes considered, whereas a value near 1 indicates that they vary widely.

Using this equation, we calculated similarity measures for each combination of *mobiTopp* agents and MINI E field trial participants. To calculate one average distance measure for each *mobiTopp*

Table 2. Logit model estimation results for the EV suitability model. Database: *CUMILE*. Probability that a car is driven more than 90 km/day on 12 or fewer days per year.

Predictor	Coefficient	Standard Error	Pr > ChiSq	Odds Ratio
Intercept	-0.510	0.381	0.181	-
Gender				
Male	-0.508	0.086	0.000	0.601
Female	[ref]	[ref]	[ref]	[ref]
Commuting Distance				
No commuting	1.560	0.357	0.000	4.758
< 10 km	2.034	0.343	0.000	7.648
10 km to < 20 km	2.022	0.351	0.000	7.553
20 km to < 30 km	1.832	0.364	0.000	6.248
30 km to < 40 km	1.837	0.385	0.000	6.277
40 km to < 50 km	0.687	0.482	0.153	1.988
> 50 km	[ref]	[ref]	[ref]	[ref]
Car in the Household				
One car	-0.510	0.093	0.000	0.600
More than one car	[ref]	[ref]	[ref]	[ref]
Spatial Structure				
Rural region	0. 208	0.091	0.020	1.232
Suburban region	0. 297	0.093	0.000	1.345
Urban region	[ref]	[ref]	[ref]	[ref]
Employment Status				
Employed: full time	-1.084	0.155	0.000	0.338
Employed: part time	-0.844	0.161	0.000	0.430
Employed: temporarily unemployed	0.133	0.235	0.573	1.142
Education: in school, at university, in further education	-1.314	0.284	0.000	0.269
Education: in vocational education	-0.806	0.373	0.030	0.447
Not employed: homemaker	-0.118	0.216	0.590	0.889
Not employed: retired	[ref]	[ref]	[ref]	[ref]
No information	-1.211	0.497	0.010	0.298
Household Size				
One person	[ref]	[ref]	[ref]	[ref]
Two persons	-0.578	0.103	0.000	0.561
Three and more persons	-0.490	0.122	0.000	0.613

agent i, we used the arithmetic means of all $d_{ij}$for the agent i with the resulting MINI E participant combinations. The probability of interest in EV ownership P_{in} is represented by this average similarity measure:

$$P_{in}(i) = \frac{1}{J} * \sum_{j=1}^{J} s_{ij}, \tag{2}$$

where J is the number of participants in the MINI E dataset. From $0 \leq d_{ij} \leq 1$, it follows that $0 \leq P_{ij}(i) \leq 1$. Thus, $P_{in}(i)$ can be interpreted as a probability.

The EV interest model shows that male *mobiTopp* agents between 40 and 50 years old who are employed and have an available household income above 3.000 /month and commuting distances of less than 20 km have the highest interest in EV ownership. Agents with EV interest usually own medium or large cars.

4.2.3 Combining both models

To determine whether a *mobiTopp* agent is going to own and use an EV, we calculated an EV ownership probability P_{own} for each agent. Previous research (Chlond et al., 2014; Wietschel et al., 2012) shows that potential users are heterogeneous in their preferences and travel behaviour: people who are interested in buying an EV and people who are suitable to drive an EV based on their travel behaviour are often not identical. In order to privilege those who meet both conditions, we combined EV usage suitability and EV interest in an EV ownership model as follows:

$$P_{own} = P_{su} * P_{in} \tag{3}$$

Thus, we ensure that agents matching only one condition have a lower likelihood of owning an EV.

4.3 The EV usage model

The EV usage model simulates the EV battery level and includes discharging during usage and charging when stopped at a location with charging facilities. The availability of charging facilities is scenario-dependent, and scenarios with facilities at home, at work and/or in public can be simulated. A car immediately starts charging when parked at a location with charging facilities. It charges using the full charging power available, as defined in Table 3, until the battery is fully charged or the car is used again. This corresponds to the dumb charging scheme (Waraich et al., 2013). Discharging and charging of the battery is modelled linearly.

The limited range of BEVs is also taken into account, since BEV users can only use their BEVs to reach destinations within the battery range. This restriction affects the destination choice and the mode choice model. The destination choice model described in Section 3.2.1 has been refined. For discretionary activities (e.g., shopping or leisure), the BEV user can only choose destinations within the BEV range, given that the car must have enough energy to also return home. A safety buffer of 33% of the remaining range is kept to account for possible additional discretionary activities and range anxiety. In the mode choice model, only trips starting at home are relevant. Otherwise, there is no mode choice decision involving a BEV. For trips starting at home, the mode choice model has been modified so that the mode car is not available for destinations beyond the BEV range (once again, accounting for the need to return home). This also applies if the only available car is a BEV.

All in all, the EV usage model represents a robust approach in which EV characteristics are regarded as constraints. Given the lack of empirical data on how drivers deal with restricted range, this approach seems most practical for our objective.

4.4 Scenarios

As mentioned in Section 3, our study focuses on the region of Stuttgart, Germany in the year 2025. To assess the effects of a growing EV fleet, we use three scenarios. These were defined in the project EVREST as an external framework (Stark et al., 2014) and differ only in the share of EVs in the car fleet; other input parameters remain constant.

The scenarios shown in Table 3 are based on research from the project EVREST (IFSTTAR-LTE et al., 2012). Here, we further distinguish between BEVs and EREVs. The method of forecasting the car market shares is described in Stark et al. (2014). For our scenarios, we assume that the car fleet structure of the Stuttgart metropolitan region is similar to the car fleet structure of Germany as a whole. We also assume that only home charging with a charging power of 3.7 kW is possible. The cars were assigned to *mobiTopp* agents using the model described in Section 4.2. To reproduce the market shares of EVs for the three scenarios, the intercept in the EV Usage Suitability model was iteratively adjusted until the percentages of EVs closely matched the percentages of the scenario specifications (deviations: 0.2-0.9 percentage points).

Table 3. Scenario specifications and definitions for the *mobiTopp* simulation

	Scenario 1	Scenario 2	Scenario 3
Share of EREV & BEV on the car fleet	1% BEV & 5% EREV	1% BEV & 7% EREV	2% BEV & 12% EREV
Recharging possible	At home	At home	At home
Charging power	3.7 kW	3.7 kW	3.7 kW
Range of BEVs	BEV: 115 km	BEV: 115 km	BEV: 115 km

5 Results

To assess the effects of a growing EV fleet, we focus on three dimensions: EV distribution among car owners, EV usage characteristics and the resulting electrical power demand.

5.1 EV ownership

We analysed the socio-demographics of EV owners in *mobiTopp* for the different EV shares in Scenarios 1 and 3. Here, we defined a measure of penetration, calculating the ratio of the share of EVs and the share of all cars for each socio-demographic group. For example, a value greater than one means that the penetration of EVs in the considered group is higher than the average EV penetration and that EVs are overrepresented in this group. We also compared the socio-demo-graphic factors gender, age, commuting distance and cars per household.

Table 4 and Table 5 are contingency tables for Scenarios 1 and 3. In both scenarios, non-commuters are more likely to own an EV. Considering the high odds ratios in Table 2 for agents with a short commuting trip, EVs are unexpectedly underrepresented in these groups. An explanation for this underrepresentation could be that commuting trips generally require an occupation, so that the odds ratio for employed agents is lower than one. Furthermore, agents who live in a household with two or more cars are slightly more likely to own an EV. One reason for this is that second cars have shorter average trip lengths and are thus more suitable for EV usage.

Table 4. EV penetration ratios for different socio-demographic groups of car owners (<1 means EV usage underrepresented; >1 means EV ownership overrepresented), Scenario 1

		Cars per household					
		1			2		
		Commuting distance			Commuting distance		
Gender	**Age**	**<10 km**	**>10 km**	**no comm.**	**<10 km**	**>10 km**	**no comm.**
	18-29	0.41	0.30	1.91	0.41	0.28	1.45
	20-39	0.40	0.27	1.43	0.64	0.32	1.77
Male	40-49	0.49	0.29	1.59	0.64	0.39	2.04
	50-64	0.45	0.27	1.75	0.56	0.37	2.01
	65 +	0.68	n.a.	1.84	0.98	n.a.	2.36
	18-29	0.46	0.30	1.51	0.53	0.41	1.73
	20-39	0.60	0.41	1.36	0.86	0.53	1.91
Female	40-49	0.75	0.47	1.83	1.07	0.63	2.28
	50-64	0.73	0.53	1.66	1.03	0.55	2.10
	65 +	0.91	0.76	1.61	1.00	n.a.	1.99

In both scenarios, agents between 18 and 29 years of age are least likely to own an EV. Possible reasons are the higher prices of EVs and the lower average income of this group. Although age is considered only in the EV interest model, this effect is noticeable in the model results.

The shares of EVs in Scenarios 1 and 3 show that EVs are distributed more evenly between the socio-demographic groups in Scenario 3. Thus, the greater the number of EVs, the more equal is

Table 5. EV penetration ratios for different socio-demographic groups of car owners (<1 means EV usage underrepresented; >1 means EV ownership overrepresented), Scenario 3

		Cars per household					
		1			2		
		Commuting distance			Commuting distance		
Gender	**Age**	**<10 km**	**>10 km**	**no comm.**	**<10 km**	**>10 km**	**no comm.**
	18-29	0.68	0.56	1.37	0.67	0.58	1.57
	20-39	0.73	0.55	1.65	0.98	0.66	1.91
Male	40-49	0.82	0.62	1.73	1.00	0.74	1.95
	50-64	0.77	0.56	1.62	0.91	0.69	1.75
	65 +	0.92	0.59	1.52	1.13	0.75	1.72
	18-29	0.68	0.55	1.06	0.69	0.63	1.17
	20-39	0.83	0.70	1.14	1.07	0.81	1.24
Female	40-49	0.99	0.77	1.37	1.21	1.00	1.51
	50-64	0.90	0.83	1.16	1.14	0.96	1.32
	65 +	0.82	0.74	0.99	0.88	0.80	1.14

their distribution among car owners. This result supports Rogers idea of an innovation adoption lifecycle for new technologies (Rogers, 2010). He concludes that innovators and early adopters are the first buyers when a new technology enters the market. These early buyers usually belong to several particular socio-demographic groups. As the technology then spreads, more and more people with heterogeneous social-demographic features buy it. In summary, *mobiTopp* agents without a regular commuting trip, especially retirees, appear to be more likely to own an EV in 2025, based on the results of our EV ownership model. As EV market share rises, the owner profile changes from early adopter to late majority, which results in more heterogeneous socio-demographics.

5.2 EV usage

To evaluate EV usage, we aggregated the car trips to car trip chains. We defined a car trip chain as a sequence of car trips between two home activities. Thus, a trip chain always starts and ends at home. Figure 2 shows the average trip chain length (diamonds) and the 25%, 50% and 75% quantiles (grey bars) of the trip chain lengths for each type of car in each scenario.

For conventional cars, the distributional properties do not differ. The average length of the trip chains is 40.1 km in all scenarios. For EVs, however, the trip chain lengths increase with higher EV shares in the car fleet. This can be attributed to the fact that agents with longer commuting distances are also taken into account as EV owners in Scenarios 2 and 3. Since EREVs have the same range as conventional cars, the average trip chain length of EREVs is close to that of conventional cars. In Scenario 1, the average trip chain length is 36.2 km, whereas in Scenario 3, it is 37.8 km. In all scenarios, the average trip chain length of BEVs is approximately the half of the average trip chain length of EREVs.

5.3 Electrical power and energy demand from EV usage

The results in Figure 3 show the electrical power consumption over one week for the three scenarios. These curves are based on the assumption that a car starts charging immediately after being parked at a location with charging facilities with a charging power of 3.7 kW. Compared to the overall electrical power consumption, the consumption due to EVs is still relatively low.

There are two reasons for the increasing electrical power demand for the three scenarios. First, the number of EVs increases. Second, the energy demand per car increases due to higher average EV mileages. For EREVs, the average weekly energy demand is 27 kWh in Scenario 1 and 31 kWh in Scenario 3 and for BEVs, the average weekly energy demand is 12 kWh in Scenario 1 and 14 kWh in Scenario 3.

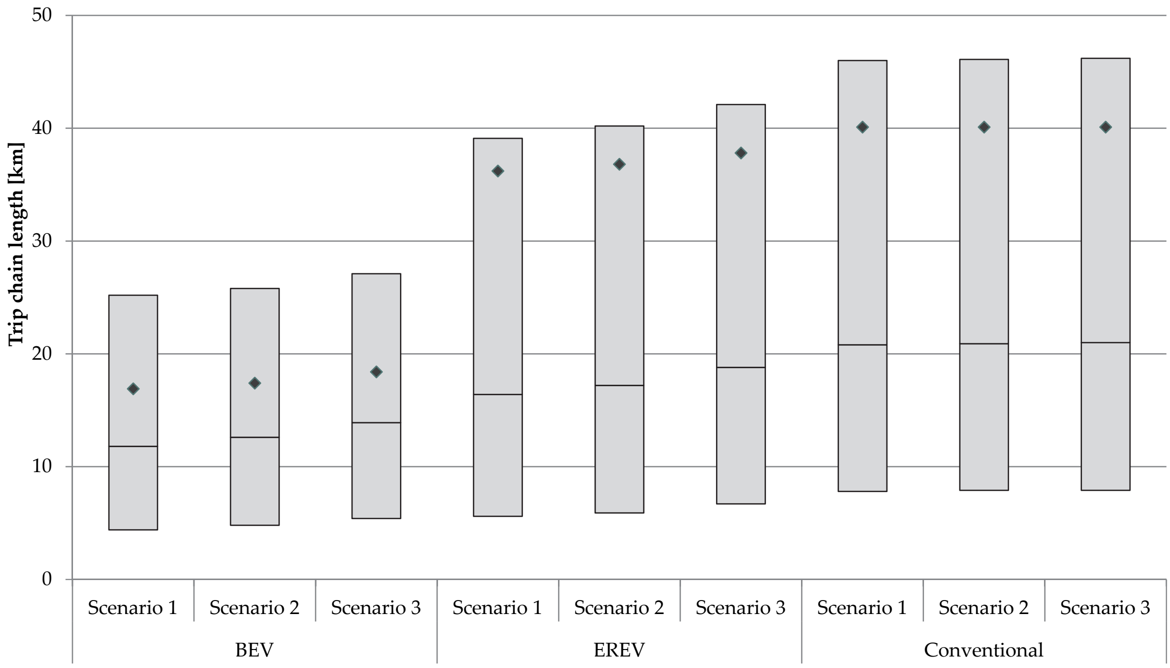

Figure 2. Distribution of car trip chains, differentiated by scenario and propulsion system (mean (diamond), median (line), upper and lower quartile (box))

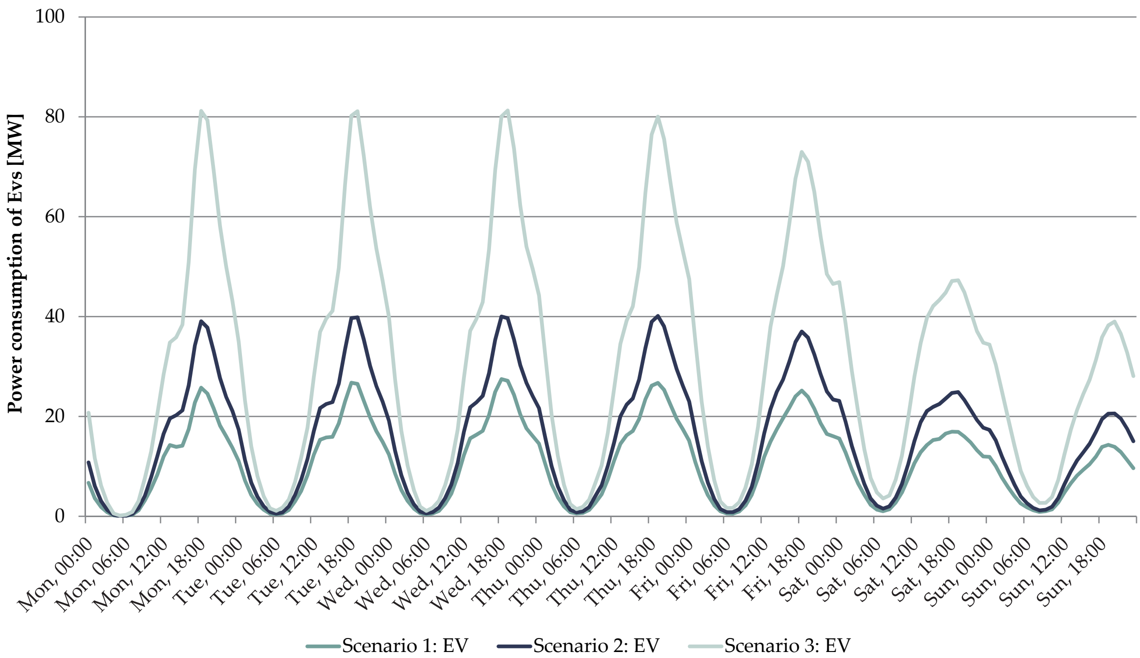

Figure 3. Temporal resolution of the electrical power demand in the model region by EREV and BEV usage for the three scenarios

In all scenarios, the peak hour is around 6 p.m., the time people return home and plug in their EVs. Although the electrical power demand for EV charging is relatively small, the temporal overlap of the load peaks could cause problems in some areas with a high share of EVs. The electrical power consumption differs over the course of one week. From Monday to Thursday, consumption is similar (see Figure 3). On Fridays, the load peak is about 10% lower, but there is a second peak around midnight due to the Friday evening weekend traffic. On Saturdays and Sundays, the load peak is approximately 50% of the working day peak, since there are no commuting trips.

6 Conclusion

We used the microscopic travel demand model *mobiTopp* to simulate the effects of different EV market penetration scenarios over a simulation period of one week. To integrate EVs into *mobiTopp*, two extensions were necessary: an EV ownership model and an EV usage model. The EV ownership model is a combination of a multinomial logit model, which assesses a car owners suitability to use an EV, and a similarity measure model, which assesses the car owners acceptance of EVs. Data from *CUMILE* and data on EV user characteristics from the MINI E Berlin field trial were used to construct this model. For the EV usage model, the destination choice model and the mode choice model were modified to account for the limited range of BEVs. The battery levels of EVs were modelled explicitly. We defined and analysed three scenarios with different BEV and EREV market penetrations. Our analysis of EV ownership, EV usage and EV electrical power demand show the following results for growing EV penetration. First, EV ownership is distributed more evenly between the socio-demographic groups in Scenario 3 than in Scenario 1. However, in all scenarios, those agents without commuting trips are more likely to own an EV. Second, the results for EV usage indicate that the average trip chain length of BEVs is much lower than that of EREVs and conventional cars, due to their limited range. Nevertheless, the trip chain lengths of EVs rise slightly with increasing market share. Third, the results for EV electrical power demand show that the load peaks of EVs and the general load peak, which is around 6 p.m., overlap on working days. This might cause a temporal and/or spatial overload of the electric grids. Furthermore, we show that the increase in EV power demand is not just caused by the higher market share. In summary, our *mobiTopp* model extensions represent a promising approach to assess the impact of EV ownership and usage on the field of transport. However, we recognize that the current models are still not advanced enough to reflect all the important factors. For example, the limited range of BEVs and the recharging process lead to more complex user behaviour than is reflected in the current approach. Nor does separate treatment of destination and mode choice permit vehicle characteristics, especially EV range limitations, to be included in both choice models equally. Thus, we need to develop a combined destination and mode choice approach that explicitly considers the characteristics of BEV usage.

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