HOW MUCH RANGE IS REQUIRED? A MODEL BASED ANALYSIS OF POTENTIAL BATTERY ELECTRIC VEHICLE USAGE

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ABSTRACT

Promoting electric mobility has become a prominent measure to reach the goal of reducing carbon dioxide in the transportation sector. However, the sales of battery electric vehicles (BEVs) are still low. The main reasons hampering the success of electric vehicles are probably insufficient user acceptance due to range limitations and high purchase costs. Hence, the crucial question is to find a battery size that is both large enough to provide sufficient range and small enough that it is not cost prohibitive. Our work addresses this question from the user perspective and aims to identify the BEV range that is necessary to satisfy most of the mobility needs by use of the agent-based travel demand model mobiTopp. Seven scenarios with varying BEV ranges have been simulated. The results show that a range of 150 km forces major adaptations of travel behavior and is, for this reason, there is a significant barrier to a broad acceptance. With a range of 400 km and above, the necessary adaptations of travel behavior are small. However, for most cars of this configuration, the charging state of the batteries do not come below 50% within one week. Thus, considering battery purchase costs and sustainability, 250 km or 300 km could be justified as a sufficient range, which satisfies already most of the mobility needs for mandatory activities.

INTRODUCTION

In recent years, the optimal range of Battery Electric Vehicles (BEVs) has been an emerging topic. This shows the difficulty of finding the "sweet spot" of a sufficient range setup that is at the same time sustainable with regard to the ecological footprint of battery production (*1*) and cost-effective (*2*). An investigation of optimal BEV range is hence important to help developing sustainable vehicle concepts. Larger batteries (i.e. higher range setups) are related to a larger ecological footprint (*1*). The main reason is that the production of a BEV consumes more resources compared to a conventional internal combustion vehicle (ICV) (*3; 1*). Only because of the lower environmental impact during vehicle lifetime, the BEV turns out to be the more sustainable vehicle concept (*4*). For this reason, an optimal battery capacity should provide the smallest range accepted by potential customers.

Several studies have been conducted aiming to identify the optimal range of BEVs. These studies either analyzed the BEV usage of early adopters (*6; 7; 5*), the usage of ICVs (*8; 9*) or carried out stated preference interviews (*10*). In the present work, we pursue a different approach in order to identify a sufficient BEV range to satisfy most of the mobility needs: the application of a microscopic travel demand model. The agent-based travel demand model mobiTopp is used to simulate the travel behavior of BEV users in the greater Stuttgart area, Germany. A scenario where all persons are using ICVs serves as reference case. In seven scenarios, the ICVs were replaced by BEVs, while each scenario used a different BEV range (between 150 km and 600 km). The limited range of the BEVs then forces the agents to adapt their travel behavior. We analyze these changes in travel behavior between the different scenarios based on mode used and distance travelled by car. We argue that the acceptance of the limited BEV ranges increases with a decreasing necessary adaption of travel behavior.

The remainder of the paper is organized as follows. First, we review relevant studies on required BEV ranges. The simulation framework mobiTopp is then described in the following chapter. Further, we outline the model extensions of mobiTopp for BEV usage followed by the model results and a conclusion.

LITERATURE REVIEW

Various studies have examined the absolute value of preferred BEV range. They have shown that potential customers prefer vehicles with a considerable higher range than they actual need in their daily life. For example, Bunzeck et al. (*11*) found that their sample of German residents preferred an average range of 328 km, although more than 80% of them did not drive more than 100 km a day. Hence, there is evidence for a large gap between range preferences and range needs, even though this gap can be expected to be smaller with increasing experience with limited-range mobility (*12*).

Other studies examined this issue by analyzing the car usage of ICVs. According to Pearre et al. (*8*), a BEV with a range of 160 km (100 miles) would meet the travel needs of about one third of all drivers in their sample when they would be prepared to make adaptations six times a year. In their analyses this value decreased to 9% when individuals were not willing to make any adaptation. Hence, even small behavioral adaptations could cause a large increase of the potential BEV market share. Chlond et al. (*13*) also analyzed the use of private cars from a longitudinal perspective over one year based on a modelling approach and concluded that 13% of the German private car fleet do not exceed 100 km on one day over a full year. Tamor, Gearhart and Soto (*14*) concluded from their analysis of real-world vehicle usage that an introduction of BEVs into the market is not only restricted by the electric range itself, but also by individuals' willingness to adapt their behavior in case of an insufficient vehicle range. This refers to the need to find alternative transportation modes when their range needs exceed vehicles' range, for example to use another household vehicle, the railway or a rental car.

Beside the users' requirements, one also has to focus on the future characteristics of BEVs and especially on how much range we can expect from BEVs in the future. In the literature, different studies assume a BEV range between 150 to 250 km in the near future (*10; 15*).

Consequently, it can be concluded that the crucial indicator for determining sufficient BEV range is the share of mobility needs that have to be satisfied by the range (*8*). Interestingly, this indicator was also found as the best predictor for customers' perception of BEVs with and without a range extender (see Schneidereit et al. (*16*)).

Another approach to analyze the potential of BEV usage is the application of models. Kang and Recker (*17*) modeled the electric energy demand of plug-in electric vehicles (PHEVs) in California for different vehicle configurations and charging strategies. Their model is based on the activity-trip chains from a household travel survey, replacing ICVs by PHEVS. Galus et al. (*18*) analyzed the effect of PHEV usage on the power supply network with the help of a travel demand model. They connected the agent-based transportation simulation MATSim and a power system simulation within a feedback loop. Waraich et al. (*19*) and Waraich et al. (*20*) developed this approach further by integrating and evaluating different charging strategies ranging from "dumb" charging, where vehicles start charging just when they have arrived, to smart charging schemes, where a centralized well-informed entity optimizes the charging of the vehicles. Knapen et al. (*21*) analyzed the power demand for EV charging in the region of Flanders for charging strategies using the activity-based travel demand model FEATHERS. Mallig et al. (*22*) studied the electrical power demand caused by charging of EVs in the Greater Stuttgart Region using the travel demand model mobiTopp and found that for an uncontrolled charging strategy the peak of electricity demand for charging is superimposed on the already existing peak of electricity demand.

THE MICROSCOPIC TRAVEL DEMAND MODEL MOBITOPP

The *mobiTopp* model (*23*) is an agent-based travel demand model which implies that every person of the study area is represented as a so-called agent. On the spatial level, the model is based on zones. The temporal dimension distinguishes long-term decisions (e.g. choice of residence, workplace) and short-term decisions (e.g. destination choice, mode choice). The short-term decisions are simulated over a period of one week with a temporal resolution of one minute. Hence, *mobiTopp* consists of two major parts: a long-term model and a short-term model. The long-term model represents the conditions and the results of decisions that are stable over a longer period, e.g. population, location of home, location of workplace, car ownership, transit pass holding. The short-term model simulates the travel behavior of the population over a simulation period of one week. The modelled region is the greater Stuttgart area.

The Long-term Model

The long-term model comprises a population synthesis module, location choice for home, work, and school, a car ownership model and a transit pass ownership model. Population synthesis is performed individually for each zone. The population is generated by repeated weighted random draws of households from data of household travel surveys. The weights of the households are generated by an approach similar to the method used by Mueller and Axhausen (*24*): Based on marginal distributions of households' (household size, number of cars) and persons' attributes (age group, sex, employment status), a weight for each household is generated by an iterative proportional adjustment approach. For the household drawn from the survey data, a corresponding household is created in the model. For each person of the survey household a corresponding agent is created in the model. Each agent inherits the activity program (the sequence of activities with the attributes type, planned start time, and duration) of the corresponding person of the household travel survey.

As the population synthesis process works on a zonal level, the home location (on the level of zones) of each household is known after population synthesis. The next step is the assignment of workplace and school place. This step is based on external matrices representing the distribution of workplaces and school places for the inhabitants of each zone. The matrices can either be generated from statistical data or be taken from a macroscopic model.

The number of cars of each household is already the result of the population synthesis step, so the car ownership model determines the type of each car only. The type of car is differentiated by segment and engine type. The model distinguishes three car segments (i.e. small, midsize, and large) and three engine types (i.e. ICV, BEVs, and PHEVs). The car segment model is a multinomial logit model using the attributes commuting distance, sex, household size, household income, and number of cars in the household. The car engine model is a combination of a model that determines whether an electric car is suitable for an agent and a model for the propensity of an agent to own an electric car. The model is described in detail in (*25*). For the present study, however, the engine type model has not been used as only BEVs were assigned to the households.

Transit pass holding is modeled as a binary logit model using the attributes employment status, sex, number of cars divided by household size, personal car availability, and region of residence.

The Short-term Model

The short-term model simulates the travel behavior of all agents simultaneously in a chronological order. The simulation starts at Monday 0:00 and ends at Sunday 23:59. Every agent starts the simulation performing an activity, typically an at-home activity. When an activity ends, the agent inspects his activity program to find the next scheduled activity. For this activity he makes a destination choice and a mode choice. The agent then starts the trip to the next destination. When the agent has reached his destination, he starts performing his next activity.

For destination choice a distinction is made between activities with fixed locations (e.g. at home, work, school) and activities with flexible locations (e.g. leisure, shopping). An actual destination choice is only made for activities with flexible locations. For activities with fixed locations the location assigned in the long-term model is used. For the activities with flexible locations the destination choice is made by a discrete choice model, using an approach similar to a gravity model, which does not only take the travel time and cost to reach the next possible destination into account, but also the travel time and cost from the possible next destination to the next known destination of an activity with fixed location. The model is described in more detail in (*23*).

The mode choice model in *mobiTopp* distinguishes the modes walking, cycling, public transportation, car passenger, and car driver. Only the main transportation mode for each trip is modeled, that means there is no mode change during a trip. The mode choice model is a multinomial logit model based on the variables time, cost per kilometer, car availability, season ticket ownership, activity type, weekday, household type, employment status, trip length, and commuting distance, see Kagerbauer et al. (*26*). An important aspect in *mobiTopp*'s mode choice model is the realistic representation of the actual available choice set. The full choice set is only available when the agent is at home and a car is available. When the agent is not at home and the mode of the last trip has been car driver or cycling, only the mode used for the last trip is available. When the agent is not at home and the last mode was neither car driver nor cycling, then just the modes walking, public transportation and car passenger are available.

Simulation of BEVs

In mobiTopp, cars are implemented as distinct entities for which fuel level and odometer mileage are simulated. For BEVs, battery capacity, state of charge, energy consumption, as well as charging and discharging of the battery are modeled. The battery capacity, state of charge, and the energy consumption determine the remaining range of the BEV. When the BEV is used, the battery discharges. When the BEV is parked at a location where charging is possible, the car will charge if the state of charge is below 90%.

The limited range of BEVs is considered by a restricted choice set for BEV drivers in the destination and the mode choice model, depending on the actual state of the agent. In destination choice, a restricted choice set will be used if the agent is committed to the mode car driver and is using a BEV for the current tour. In this case, the choice set contains only the destinations that are within the BEV range, taking into account that the car needs to have enough energy remaining to return at home. Concerning BEVs in the mode choice model, only trips starting at home are relevant. For the other cases, BEVs have already been considered in the destination choice model. For trips starting at home, the choice set does not contain the mode car driver when the only available car is a BEV and the destination of the trip is beyond the BEV range, again, taking into account the necessity to return home afterwards.

The availability of charging facilities is configurable and can be defined for each zone and activity type. This enables a wide range of possibilities for the simulation of charging behavior, e.g. with charging facilities only at home or with charging facilities at home and at work. In the model, a car always starts charging, when parked at a location with an available charging facility and a charging state below 90%. It stops charging either when the battery is full or when the car is used again.

RESULTS

The study area used for the work presented is the Greater Stuttgart Area in Germany. This area has a population of about 2.7 million inhabitants owning 1.3 million private cars. In order to assess which BEV ranges are required, simulations of the travel behavior of the population and the usage characteristics of cars have been run using mobiTopp. A scenario for the year 2025 with only ICVs has been simulated as reference. For the assessment of the BEV range seven scenarios with different BEV ranges (150 km, 200 km, 250 km, 300 km, 400 km, 500 km, 600 km) have been simulated in addition. These scenarios were compared to the reference scenario in view of how much adaptation of the travel behavior is needed for different BEV ranges. In order to obtain a comprehensive picture of the potential of the BEV usage, all ICVs were replaced by BEVs in these scenarios. As the introduction of public charging infrastructure is still slow, only charging at home was modeled in the simulated scenarios. A charging rate of 3.7 kW/hour was defined for all charging facilities.

In the upcoming sections, we analyzed the variation of the following travel key figures resulting from varying BEV ranges: daily mileages on an individual level, as well as weekly mileages, tour characteristics and state of charge on car level. In the destination choice and in the mode choice, trip purposes with fixed and flexible activity locations were treated differently. Hence, we also distinguished in our analysis between mandatory (commuting to work and education, business and service trips) and discretionary tour purposes (shopping and leisure activities, running errands and round trips). Thus, we determined the main trip purpose for home-based tours by defining the main purpose of a tour by the purpose of the trip to the activity with the longest duration.

Daily Mileages of Car Users

A comparison of key travel figures of persons, such as mileage per day and the modal split, gives a first impression whether and how the application of BEVs of different ranges influences the personal travel behavior. In these analyses, we focused on agents with a car in the household who hold a driving license, since only this person group is directly affected from BEV usage as the BEV is in their mode choice set.

FIGURE 1a) shows that the mileage per day and person for the 150 km range scenario is as far as 3 km per day below the key figure of the ICV scenario. Considering only the BEV scenarios, the biggest change of the car mileage per day is between the 150 km and the 200 km range scenario. This suggests that already a range extension to 200 km shows considerable effects. Furthermore, the figures indicate a mode shifting from car as driver to other modes for low vehicle ranges. These BEVs might match the travel behavior of their owners worse than ICVs since destinations that are more distant are chosen less often which shrinks the daily mileages travelled by car (i.e. with the BEV). Further, the BEV may not be included in the mode choice set for distant activities as well. Consequently, persons have to use other modes, such as public transportation.

The FIGURE 1b) and c) illustrate that the limited BEV range has a greater influence on discretionary activities than on mandatory activities. For the 150 km BEV scenario, the daily car mileages decrease by 10 km for the discretionary activities and by only 4 km for the mandatory activities compared to the ICV scenario. With increasing BEV ranges, the travel figures approach gradually to the ones of the ICV scenario. The modal split and the daily car mileages of the 500 km and 600 km scenarios match the ICV scenario, especially for mandatory activities. However, the relatively small enhancements of these travel figures between 300 km, 400 km and 500 km might not justify the extra costs of higher battery ranges. Hence, depending on the individual needs, the optimal range for the majority of users is somewhere between 300 km and 400 km.

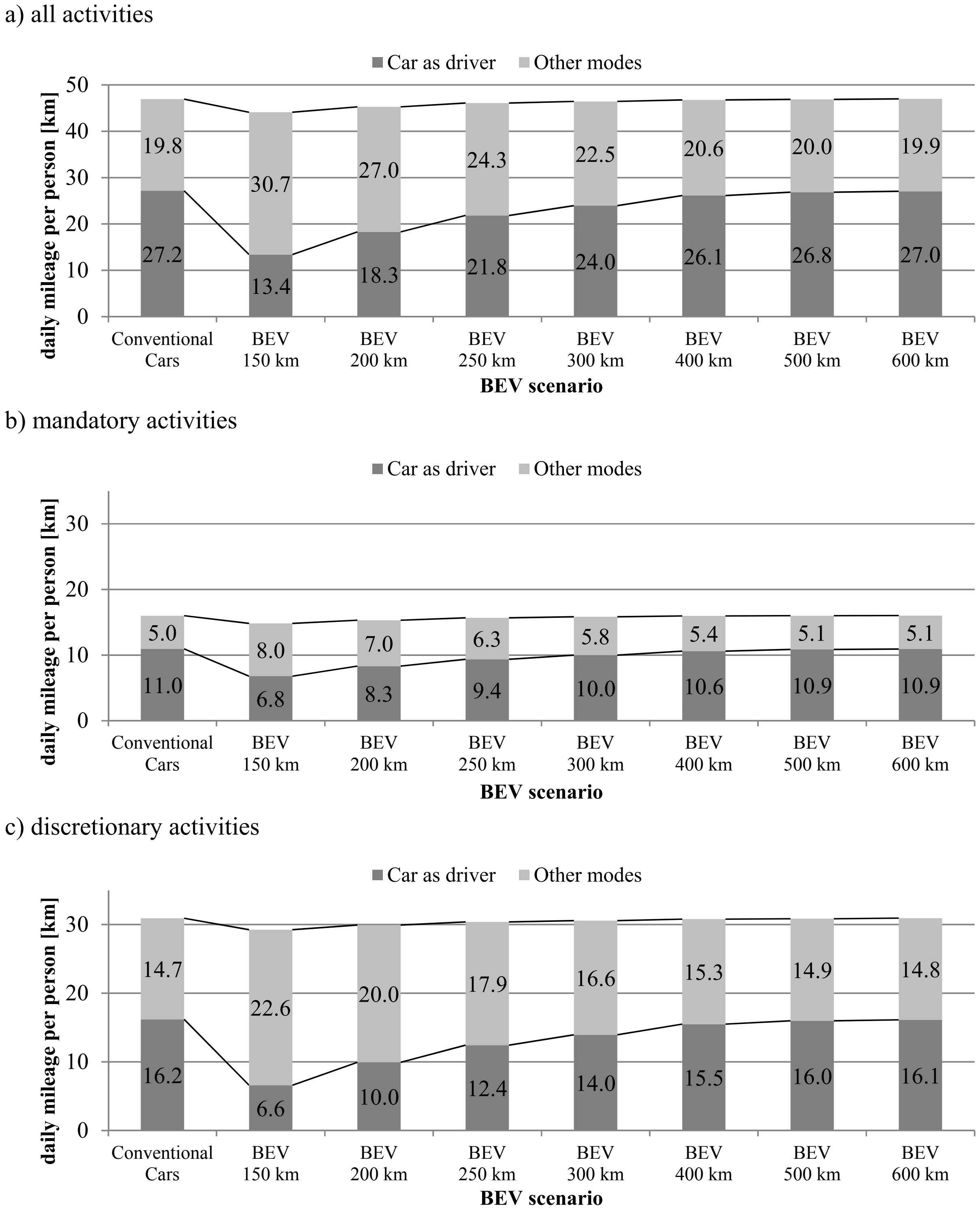

FIGURE 1 Daily mileage per person, distinguished by car as driver and other modes; different BEV scenarios; for a) all activities, b) mandatory activities and, c) discretionary activities.

The Variation of Weekly Car Mileages

The previous analysis focused on the travel behavior of car drivers, but not on the car usage characteristics. Since each car can be used by multiple persons, e.g. different household members, we have also examined key travel figures on the car-level (user-level vs. car-level). Hence, we studied the total weekly mileages of the cars and compared the distributions of their weekly mileages. FIGURE 2. Illustrates the cumulative distribution of the weekly mileages for all trips as well as differentiated by mandatory and discretionary activities.

As expected, the distribution of weekly driven kilometers of BEVs approaches the distribution of ICVs with an increasing range. To quantify the differences between the distributions, we used the root-square mean deviation (RMSD) comparing the BEV scenarios with the scenario with ICVs. For a BEV range of 150 km, the RMSD is highest with 15.7 percentage points. With an increasing BEV range, the RMSD decreases to 0.2 resp. 0.1 percentage points for the 500 km resp. 600 km BEV scenario. However, the RMSD already decreases below 1.0 percentage point in the 400 km BEV scenario (RMSD: 0.8 p.p.). As aforementioned, we argue that the improvement of 0.6 percentage points in RMSD does not a range extension to 500 km.

For trips with mandatory and discretionary activities, the RMSD is 18.8 percentage points resp. 18.6 percentage points for BEVs with a range of 150 km. The BEV scenarios' cumulative distributions approach the one of the ICVs with an increasing range. However, there are slight differences in the RMSD for the 200 km, the 250 km and the 300 km BEV scenario regarding the mandatory and the discretionary activities. The values of the RMSD for these scenarios show, that the effect of a lower range is less distinctive for mandatory activities.

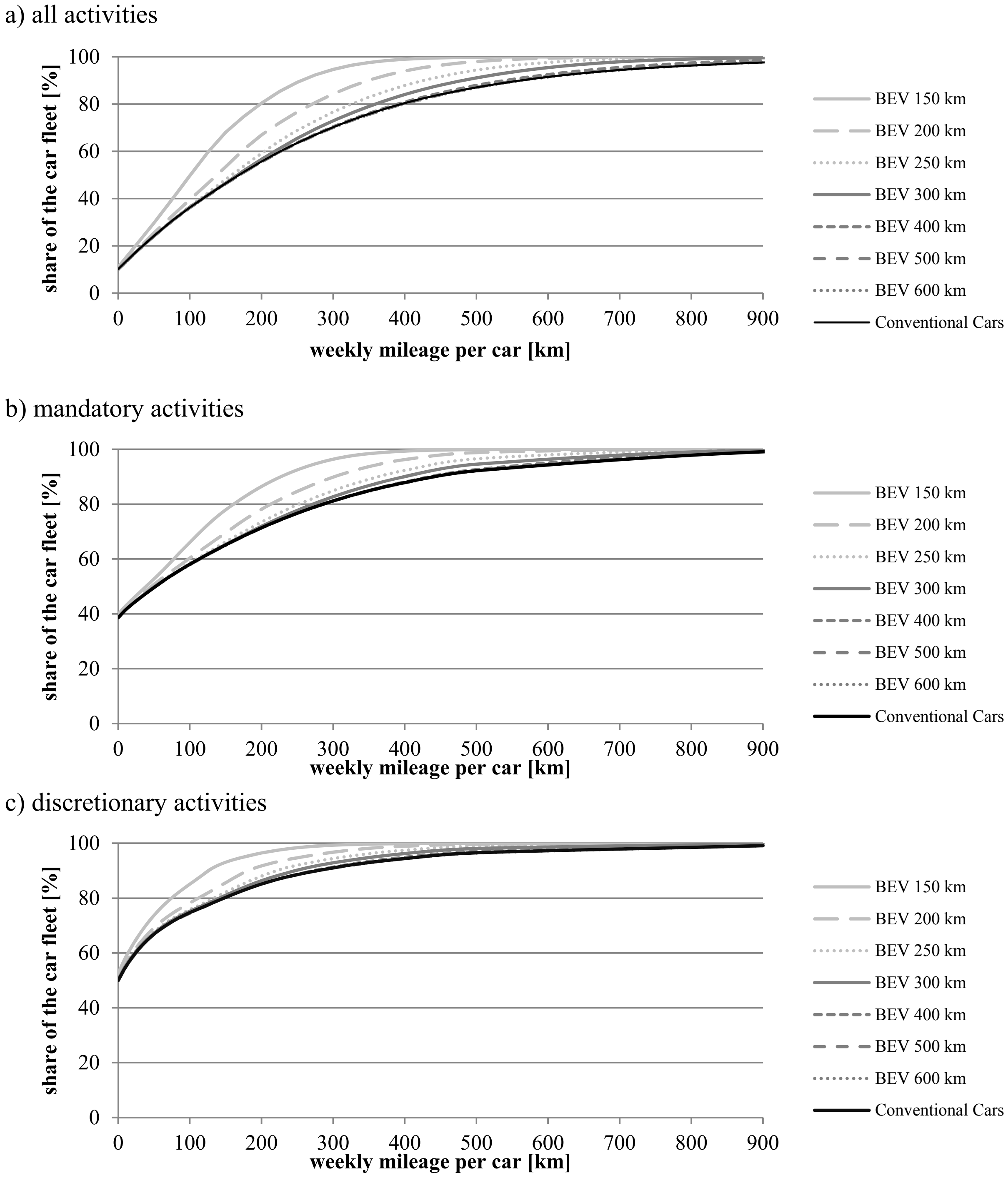

FIGURE 2 Cumulative distribution of the weekly car mileages; different BEV scenarios; for a) all activities, b) mandatory activities and, c) discretionary activities.

Car Mileage Variations on Home-based Tours

Not only the variation of the weekly mileages, but also the variation of the home-based tours (i.e. tours starting and ending at home) might give an indication for optimal ranges of BEVs. Hence, we analyzed both, the number and the mileages of home-based tours. Additionally, we used Cohen's *d* to assess the effect size of the difference in mean values of the tour mileages.

As shown in TABLE 1a), the mean, the median and the 99% quantile of the kilometers per tour differ and increase with a growing range. Whereas the median increases from 16.6 km in the 150 km BEV scenario to 20.5 km in the ICV scenario, the mean increases from 23.3 km to 39.4 km. Further, the 99% quantiles increase from 113.8 km to 223.4 km. Thus, it can be assumed that the high means of the scenarios with a higher range are primarily caused by few long-distance tours only. Lower range causes fewer tours as well. On average, ICVs are used for 6.0 tours within one week. In case of a BEV range of 150 km, this figure decreases to 5.1 tours per week.

TABLE 1b) and c) illustrate that this effect can also be observed for tours with mandatory and discretionary main activities. The mean values of the two activity types differ only slightly (mand.: 24.8 km – 40.1 km; discr.: 20.2 km – 37.7 km). In contrast, the median values of the two activity types show large differences (mand.: 19.2 km – 23.2 km; discr.: 12.0 km – 15.1 km). A comparison between tours with discretionary activities and tours with mandatory activities indicates that the variation of tour lengths is greater for discretionary activities whereas the average tour lengths are higher for mandatory activities. However, for all activity types, there are only slight variations for the tour key figures for the BEV ranges higher than 400 km. Thus, we assume again that the effort to increase the BEV range above 400 km is too big, compared to the benefits. The lower variation in tour lengths of mandatory activities even supports the conclusion that in many cases, an even lower range (e.g. 250 km or 300 km) would be sufficient for BEVs, which are mainly used for these types of tours.

Regarding the effect size, there was no difference between the activity types. For the scenarios with a BEV range of 150 km resp. 200 km, the effect size was small (Cohen's *d* all/discr.: 0.4/0.2, Cohen's *d* mand.: 0.4/0.2). For all other scenarios, there is no measurable effect.

TABLE 1 Distributional Values for the Mileage of Home-based Car Tours for a) All Activities, b) Mandatory Activities, and c) Discretionary Activities [km]

	ICV	BEV 150	BEV 200	BEV 250	BEV 300	BEV 400	BEV 500	BEV 600
Mean	39.4	23.2	29.5	33.6	36.0	38.3	39.1	39.3
Median	20.5	16.6	18.1	19.0	19.8	20.3	20.5	20.5
99% quantile	223.4	113.8	159.7	188.0	203.6	216.0	221.2	221.3

a) All Activities

	ICV	BEV 150	BEV 200	BEV 250	BEV 300	BEV 400	BEV 500	BEV 600
Mean	40.1	24.8	30.6	34.6	36.9	38.9	39.8	39.9
Median	23.2	19.2	20.8	21.8	22.4	23.0	23.2	23.2
99% quantile	221.2	108.8	156.8	184.8	200.2	212.6	218.0	218.0

b) Mandatory Activities

	ICV	BEV 150	BEV 200	BEV 250	BEV 300	BEV 400	BEV 500	BEV 600
Mean	37.7	20.2	27.2	31.6	34.1	36.7	37.4	37.8
Median	15.1	12.0	13.0	13.8	14.3	14.9	15.1	15.1
99% quantile	225.0	119.4	162.8	191.4	207.8	219.0	223.8	223.6

c) Discretionary Activities

State of Charge on a Car Level

The analyses of car usage over one week indicate that a relatively high battery capacity of BEVs is needed in order to enable the agents to travel without greater changes in their travel behavior. However, this would entail that for most days only a small fraction of the battery capacity would be used. One the one hand, this can be interpreted negatively since the BEV would carry a large battery without really making use of its capacity most of the time (i.e. for a BEV concept to be optimally sustainable the whole battery capacity should be used frequently). One the other hand, this could also mean that a high capacity would be available for intelligent charging algorithms (i.e. controlled charging).

In order to analyze this potential, we computed the minimum state of charge per car at the start of the charging process within the simulation week. FIGURE 3 illustrates that only a very small fraction of cars utilizes its entire battery capacity regularly. In particular, less than 1% of the BEVs in the 600 km scenario reach a state of charge of less than 20% at least once in the simulation period. In the 200 km BEV scenario, at least 10% of the cars undercut a state of charge of 20% at least once a week. On average, the minimum state of charge per car is 59% for BEVs with small ranges (200 km and 250 km) and increases to 75% for BEVs with high ranges (600 km).

Consequently, the higher the range of a BEV, the lower battery capacity utilization on average. This finding indicates that larger batteries needed for larger BEV ranges might be inefficient. Hence, one would expect the lowest average minimum state of charge in the 150 km scenario. However, BEVs with a range of 150 km were used differently. The medians of the 150 km and 200 km scenario are equal, however, the mean minimum state of charge is higher in the 150 km scenario. This indicates that BEVs with a range of 150 km were used on shorter trips much more frequently. In addition, considering the results of the daily mileages of car users, we assume that these cars are used less often as well. Their users have to fall back on other modes instead due to the limited range of 150 km, whereas the results of the scenarios with a BEV range of 200 km and above indicate less fall back on other modes. Hence, a range of 150 km appears rather insufficient regarding the travel behavior.

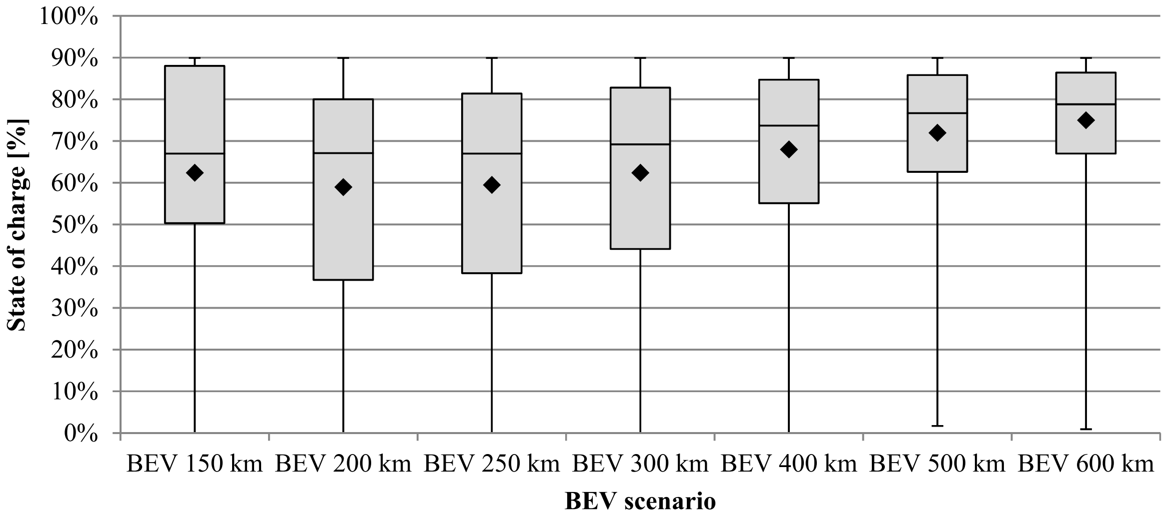

FIGURE 3 Minimum state of charge of BEVs during one week

CONCLUSION

We used the agent-based travel demand model mobiTopp to determine optimal BEV ranges. We considered the limited BEV ranges in the destination choice and in the mode choice. Seven scenarios with varying BEV ranges have been simulated in order to assess the distinctions in travel behavior for these scenarios compared to a scenario with ICVs only. The results indicate that the recommendations for required ranges strongly depend on the point of view. Our results on the variations of weekly car mileages and mileages on home-based tours suggest that a BEV with a range of 400 km or more might be necessary to comply with all mobility needs. However, if one accepts some adaption of travel behavior for mostly discretionary activities, a BEV range of 250 km to 300 km is sufficient. For those ranges, we found that BEVs could be used more or less in the same way as ICVs for mandatory activities. In addition, the analysis of battery charging illustrates that high BEV ranges lead to inefficient battery usage. Furthermore, a BEV range of only 150 km leads to many undesirable adaptions of the travel behavior which results in a high level of mode shifting.

These findings also suggest that a BEV with an economical battery capacity and hence a lower range might not be the general solution from the travel behavior perspective. Other electric vehicles concepts, such as the extended range electric vehicles or plug-in hybrid electric vehicles might match individuals travel needs better. Due to their second energy source, e.g. a small gasoline-powered motor or electrical generator in addition to the battery, they provide higher ranges for seldom occurring long distance events, which could hamper mode shifting; daily activities in the vicinity can be reached using electric power from small batteries only.

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