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Do plug-in electric vehicles cause a change in travel behavior?

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Abstract

The market diffusion of plug-in electric vehicles (PEVs) depends, besides many other factors, on how suitable these cars are for persons' every day travel behavior. We combine the outcome of two model-based approaches to derive how persons' travel behavior might change if they use PEVs. The first model *ALADIN* determines the PEV owners, who are integrated within the second model, the microscopic travel demand simulation *mobiTopp*, in order to analyze the changes in travel behavior. The results show that PEVs in today's configuration are in many cases not suitable for daily mobility patterns and the mode has to be changed for some trips instead.

Keywords: mobility system, demand, modeling, simulation, market development

1 Introduction

Due to climate change and the finiteness of fossil resources, alternative fuel vehicles have gained more and more attention in recent years. The promotion of plug-in electric vehicles (PEV) has been placed on the political agenda in various countries. Since the characteristics of PEVs differ from conventional cars (e.g. in driving range, local emissions, electric energy demand), there is a need for an assessment of the effects of a growing PEV fleet. Several effects have been investigated recently. One major research topic was the energy demand of the PEV fleet [1], charging strategies [2] and, as a consequence, the effects on the electrical grid [3, 4].

The effects of a growing PEV fleet on travel behavior has still been a marginal issue. Facing this issue on an aggregated level, vehicle ranges of 150 km and less seem to be suitable for peoples' average daily mileage of 40.9 km (Germany) [5]. Studies on a miocroscopic level, taking a logitudinal persepctive, show that this assumption is not valid. The share of cars used for long-distance-travel is underestimated when only taking cross-sectional surveys into account [6]. By considering only one survey day, 91.1 % of the German private car fleet does not exceed 100 km. This share shrinks to 13.1 % when the car usage of a full year is analyzed. Due to higher purchase costs ans lower operating costs compared to conventional vehicles, PEV purchase will be only economically reasonable, if the car has a high annual mileage. However, only 2.6 % of the representative sample covers at least 10,000 km a year while not exceeding 100 km on any day of the year.

This study aims at investigating the influence of the limited driving ranges and lower operating costs of PEVs on peoples travel behavior. Therefore, two important prerequisite have to be considered. First, since travel behavior is heterogeneous, it is important to predict well who owns a PEV. Second, the influence of PEVs on peoples travel behavior as well as the travel behavior itself has to be quantified and reproduced correctly. There have been several studies integrating PEVs in microscopic travel demand models [7, 3, 8, 1].

However, these studies either focused on the impacts of PEVs on the electrical grid or did not consider the restrictions of PEVs in the travel demand simulation. This paper presents the methodology combining a model for predicting PEV owners (*ALADIN*) and an extended version of the agent-based model *mobiTopp*, now considering range restrictions of PEVs more precisely.

2 Related Work

One aspect is the identification of potential owners of PEVs and the estimation of its market potential. Another aspect is how electric vehicles are used.

In literature, there are several ways to assess potential users of PEVs. Analyzing travel behavior, [9] used GPS data from conventional cars of 255 households to investigate how plug-in electric vehicles can match the household needs. Results suggest that a battery-electric vehicle (BEV) with a range of 100 miles should meet the needs of 50 % of the one-vehicle households participating in the survey. Other analyses are based on customer preferences. For example, [10] used the stated preferences of people living in and around Seoul for a simulation analysis of changes in car ownership in South Korea. A third approach based on total cost of ownership (TCO), is used by the *ALADIN* model used in this work [11].

An important aspect missing in most of these studies, however, is how PEVs will be used. Microscopic models are especially well suited for such analyses, due to their ability to simulate individual vehicles. MATSim was one of the first travel demand models used to analyze the usage of plug-in electric vehicles (PHEV) and their effect on electrical grid [7]. In this work, MATSim has been connected with the power system simulation PMPSS and both systems have been run iteratively. In their work, they iteratively connected the agent-based travel simulation MATSim and the power system simulation PMPSS. [12], [3], and [8] developed this approach further by integrating and evaluating different charging strategies for BEVs. In later work, a more detailed scenario of the city of Zurich is implemented. [1] used the output of the activity-based model Feathers [13] to predict energy demand and power peaks caused by PEV-charging, considering different market shares and charging strategies. Both the MATSim-PMPSS model and the approach by [1] focus on specifying the electrical power demand caused by the usage of PEVs (BEVs and PHEVs) for one day. However, neither approach explicitly considers possible changes in destination choice caused by PEV 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. Our main goal is to highlight the behavioural aspect. *mobiTopp* can account for changes in destination and mode choice due to PEV restrictions at the same time.

However, to the authors' knowledge, the combination of a model to predict PEV ownership (*ALADIN*) and travel demand model (*mobiTopp*) is unique.

3 Model Frameworks

The *ALADIN* model (**AL**ternative **A**utomobiles **D**iffusion and **IN**frastructure) is capable of simulating the market diffusion of PEVs very precisely, but has no framework for modeling travel behavior. The *mobiTopp* model is a well calibrated travel demand model, which can also simulate PEVs with their characteristics. To match both aforementioned prerequisites, we integrated the *ALADIN* results in *mobiTopp* and determined the changes in travel behavior caused by PEVs. The scenario used in the following is a model of the Greater area of Stuttgart consisting of the city of Stuttgart and the five surrounding administrative districts with a population of about 2.7 million inhabitants.

3.1 *ALADIN*

The model *ALADIN* determines the market diffusion of PEVs and their charging infrastructure based on conventional vehicle driving profiles (all car movements in at least one week) [14, 15]. For illustration, see Figure 1. We use about one million vehicle driving profiles for private vehicles [16] and about 500 for commercial fleet vehicles [17] which were prepared for their use in *ALADIN* as described in [18].

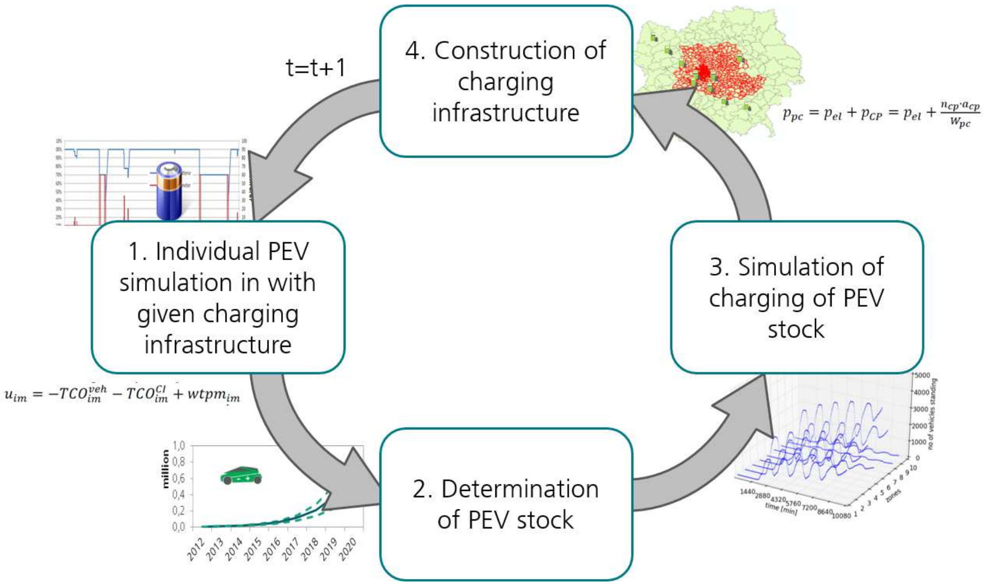

Figure 1: Flow chart of *ALADIN*

In Step 1 (Figure 1), each vehicle is individually simulated as PEV to determine whether all trips can be performed by a battery electric vehicle (BEV) and what share of electric driving would result for a plug-in hybrid electric vehicle (PHEV). The following vehicle purchase decision is based on a total cost of ownership calculation, but also includes the additional cost for charging infrastructure, the limited availability of PEVs of a certain brand and the willingness to pay more for PEVs conducted from user acceptance surveys. We determine the best vehicle option for each user in the vehicle purchase decision and can thereof derive the sales share per year as the share of PEVs being the best option in relation to all vehicle driving profiles.

By determining the best vehicle options for users in several years, the future market diffusion of PEVs can be derived (Step 2). In a consecutive simulation of the driving of all PEVs in stock (Step 3), the usage of domestic, work and public charging points can be found which is used to construct new public charging infrastructure based on the users needs (Step 4). These are considered in the vehicle buying decision in the consecutive year. Here, we use vehicle movements from the region of Stuttgart since the described data contains geographical information which we need to find out whether two cars are parked at a charging station at the same time (second part of the simulation). Altogether, we can determine the PEV and charging infrastructure diffusion until 2030 with *ALADIN*. For more detail refer to [18].

3.1.1 *mobiTopp*

mobiTopp [19] is an agent-based travel demand model, modeling every person, every household, and every car of the study area as an individual entity. Each person is represented as an agent. An agent is an entity that makes decisions autonomously, individually, situation-dependent and interacts with other agents [20]. In *mobiTopp*, agents make decisions for destination choice and mode choice. These decisions are based on discrete choice models. Interactions between agents occur indirectly through the availability of cars in the household context. When an agent uses a car of a household, the car is not available for other household members until the agent returns home. If the last available car is taken, the decision to use the car influences the mode choice options of the remaining household members.

mobiTopp consists of two parts, the long-term model and the short-term model. The long-term model comprises population synthesis, assignment of home zone and zone of workplace, car ownership, and ownership of season ticket for public transport. The results of the long-term model are considered fixed for the following short-term model. In the short-term model the agents behavior (activities and trips) is simulated simultaneously and chronologically over the simulation period. The simulation period is one week. The temporal resolution is one minute; the spatial resolution is based on zones. *mobiTopp* has been successfully applied to a study area with more than two million inhabitants and more than thousand zones [21].

The long-term model

The most relevant part of the long-term model is the population synthesis model. Households and persons are generated for each zone based on the total numbers of households and persons given on the level of zones and on the distributions of the households and persons attributes. The corresponding zone is assigned as home zone. Population synthesis is based on census data and the data of a household travel survey. The population of each zone is generated by repeated random draws of households and the associated persons from the survey data. The distributions of households and persons attributes are taken into account by an appropriate weighting of a households probability to be drawn.

The population synthesis model distinguishes 12 household types, which are the result of a Cartesian product between the attribute number of persons per household with four levels and the attribute number of cars per household with three levels. On the person level, the model uses the attributes age group, sex and employment status (fulltime, part-time, unemployed, student, homemaker, retired). The population synthesis uses a two-stage process similar to the method described by Mueller and Axhausen [22].

The short-term model

In the short-term model, the travel behavior of all agents is simulated chronologically. During the simulation period of one week, the agents perform their assigned activity programs. Each agent typically starts the simulation performing an at-home activity. When an agent has finished his current activity, he inspects his activity schedule and identifies the next activity. For this activity, he performs a destination choice. To reach this destination, he makes a mode choice out of the set of available modes. Finally, he makes the trip to the chosen destination using the selected mode. After reaching the destination, he starts performing the next activity.

In destination choice, the model distinguishes between two types of activities: activities with fixed locations (work, school, at home) and activities with flexible locations, for example shopping or leisure. For activities with fixed locations, no destination choice is made in the short-term model, since these destinations have already been determined in the long-term model. For activities with flexible locations, a destination choice is made on the level of zones using the discrete choice model.

In addition, *mobiTopp* simulates the main transportation mode for each trip. Seven modes are distinguished: walking, cycling, public transport, car driver and car passenger, as well as free-floating and station-based carsharing [23, 24]. The actual available choice set depends on the current state of the agent in terms of decisions taken earlier and partly on the actions of the other members of the same household. The most important factor is the agents current location. In general, if the agent is at home all modes are available independently of the mode used before. However, the mode car driver is not available if the agent does not hold a driving license or the households cars are currently all in use. If the agent is not at home, the available choice set depends essentially on the mode used before. If the previous mode has been car driver, station-based carsharing or cycling, only the mode used before is available for the next trip. This approach is based on the idea that a car or a bicycle that has been used at the start of a tour has eventually to return home resp. to the station. If the agent is not at home and the previous mode is one of the modes walking, public transport, free-floating carsharing or car passenger, the choice set for the next trip consists of these modes. The modes car driver, station-based carsharing and cycling are not available, since the necessary vehicle is missing. In general, to use one of the two carsharing modes, the agent has to hold a membership of the provider and a car has to be available.

The choice between the available destinations and modes is made simultaneously by a multinomial nested logit model [25].This model is based on the variables distance, travel time, travel cost, weekday, season ticket ownership, household type, and further sociodemographic variables. The characteristics of PEVs are considered explicitly in the destination and mode choice decisions. The combined model approach allows to reject these choices (destinations and the mode car), which cannot be reached or used due to the restricted range of the PEV. Further, reduced operational costs of PEVs are also taken into account.

4 Methods and Data

4.1 Data

The activity programs used during the short-term stage of *mobiTopp* are based on data collected by a seven-day survey conducted in the greater Stuttgart area in Germany [26]. Overall, the data contain information about 293,350 trips, including information about trip purpose, start time, duration, trip length and the mode used.

As input for *ALADIN*, we use the vehicle trips of *mobiTopp* that were assigned from persons to vehicles where unambiguously possible (see [18] for details).

4.2 Methods

Based on vehicle usage of the population of the Region of Stuttgart as an output of *mobiTopp*, *ALADIN* determines PEV ownerships for every year from 2020 to 2030. The results of *ALADIN* for the year 2030 were used to develop a new PEV ownership model for *mobiTopp*. The method to integrate the results of *ALADIN* in *mobiTopp* uses two steps. First, PEV owners from *ALADIN* were matched with all car owners from *mobiTopp* based on their socio-demographics. Since *ALADIN* already uses the *mobiTopp* output, sociodemographic variables and their classification match in both datasets. The result from this step is a dataset of all car owners of *mobiTopp* with their socio-demographics accumulated with the information about the engine type of the car (conventional vehicles, BEVs and PHEVs).

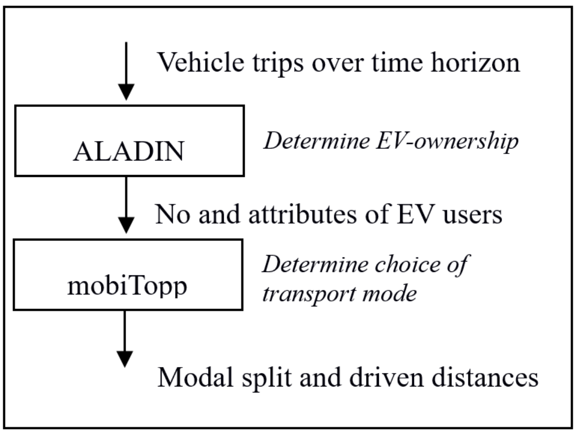

Figure 2: Modelling process

Second, a multinomial logit model (MNL) was estimated in order to analyze relevant factors and develop a scalable model for PEV ownership as part of *mobiTopp* s long-term model, based on the dataset created

Table 1: Results of the PEV ownership model

	Estimate	Standard Error	t-ratio
BEV: ASC	-5.9987***	0.0896	-66.92
BEV: Distance to work	0.0849***	0.0003	261.08
BEV: Distance to education	0.0282***	0.0009	33.18
BEV: Gender (female)	-0.0253**	0.0117	-2.16
BEV: Full-time job	0.1141***	0.0171	6.66
BEV: Part-time job	-0.1788***	0.0216	-8.26
BEV: Jobless	-0.0950*	0.0504	-1.89
BEV: Pupil	-0.2336***	0.0430	-5.43
BEV: Student	-1.2064***	0.1043	-11.57
BEV: Apprenticeship	-0.5250***	0.0467	-11.24
BEV: Age 75 to 85	-0.6493***	0.0387	-16.76
BEV: Number of cars (1)	1.8277***	0.0868	21.07
BEV: Number of cars (2)	1.4721***	0.0861	17.09
BEV: Number of cars (3)	1.7370***	0.0874	19.86
BEV: Number of cars (4)	1.4466***	0.0928	15.58
BEV: Household size (1)	0.1432***	0.0235	6.09
BEV: Household size (2)	-0.2359***	0.0218	-10.84
BEV: Household size (3)	-0.6587***	0.0239	-27.60
BEV: Household size (4)	-0.1107***	0.0228	-4.86
PHEV: ASC	-6.1904***	0.0806	-76.79
PHEV: Distance to work	0.0786***	0.0002	316.29
PHEV: Distance to education	0.0264***	0.0006	41.95
PHEV: Gender (female)	-0.0292***	0.0078	-3.76
PHEV: Full-time job	0.9010***	0.0131	68.75
PHEV: Part-time job	0.4151***	0.0155	26.79
PHEV: Jobless	-0.1502***	0.0432	-3.48
PHEV: Pupil	0.4616***	0.0283	16.31
PHEV: Student	-0.5594***	0.0582	-9.62
PHEV: Apprenticeship	0.5223***	0.0277	18.86
PHEV: Age 75 to 85	-1.2896***	0.0430	-29.99
PHEV: Number of cars (1)	2.7169***	0.0791	34.35
PHEV: Number of cars (2)	2.3361***	0.0788	29.64
PHEV: Number of cars (3)	2.5716***	0.0794	32.39
PHEV: Number of cars (4)	2.3072***	0.0813	28.39
PHEV: Household size (1)	-0.4333***	0.0149	-29.00
PHEV: Household size (2)	-0.3639***	0.0133	-27.37
PHEV: Household size (4)	-0.7508***	0.0145	-51.79
PHEV: Household size (5)	-0.0453***	0.0136	-3.33
Number of observations	1,560,150		
Log-Likelihood	-501,065		
Rho-sq	0.71		

***, **, *: significance at 10%, 5%, 1% level

in Step 1. Its choice set consists of conventional cars, BEVs and PHEVs. The influencing variables, which were found to be significant, are: distance to work, occupation, age, car per household and household size. The results (see Table 1) show that the distance to the work resp. education facility of the agent has an important influence on PEV ownership. The higher the distance to work, the higher is the possibility of PEV ownership. This corresponds with the findings mentioned above, that only cars with

a high annual mileage and seldom long-distance trips can be economically replaced by PEVs. Since trips to work or for educational purposes are recurrent trips, there is less time for long-distance events. Moreover, a higher distance to work results in higher daily trip distances and though in a higher annual mileage.
Hence, the long-term model is now able to reproduce the PEV owners determined by the *ALADIN* model for the year 2030. Consequently, the short-term model of *mobiTopp* is able to show the effects caused by the PEVs for their owners' travel behavior.

5 Results

The results show analyses of two scenarios: Scenario 1 did not include PEVs, whereas in Scenario 2 PEVs ownership was determined based on the *ALADIN* results. In total, Scenario 2 contains 20,106 battery electric vehicles (BEVs) and 43,428 plug-in hybrid electric vehicles (PHEVs). For the BEVs, we assumed a range of 115 km, considering range anxiety and auxiliary power consuming (e.g. heater, air conditioner). For PHEVs, we assume a range of 50 km for the electrical engine. Those assumptions match the ranges of today's PEVs. To keep the results of both scenarios comparable, we only compared the travel behavior of these households owning an PEV in scenario 2.

Studies show that over 80 % of charging events are performed at home [27, 28]. Further, studies found that public charging infrastructure rather has a psychological function for users than a practical function [29]. Due to the sparse usage and the uncertainties how the future of public charging will look like, we have decided to use the "worst case" in our simulation: Charging is possible only at home; charging in public and semi-public is not available. The charging power at home was assumed to be 3.7 kW.

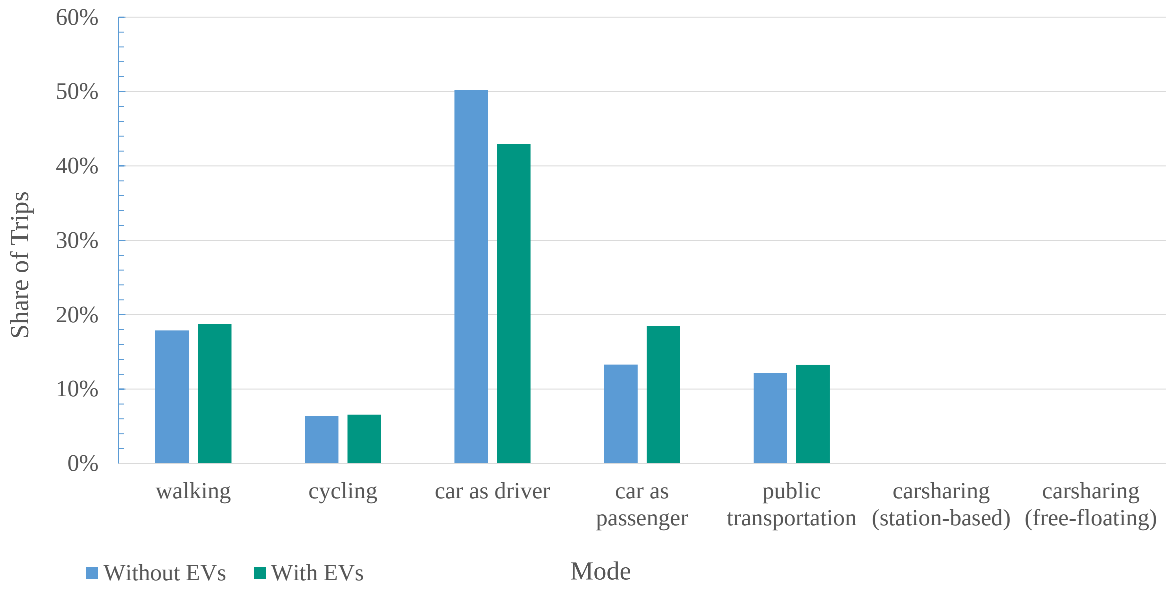

Figure 3: Share of trips by mode

Figure 3 shows the share of trips by mode for both scenarios. The mode "car as driver" is used less in the scenario 2 with PEVs. As a consequence, the usage of the other modes increases, especially the mode "car as passenger" becomes more attractive, mostly on longer trips with a bad public transportation alternative. The carsharing modes are used, however the number of carsharing trips is very small and though not visible in the diagram. The decrease in the share of trips with the mode "car as driver" may have several reasons. First, PEV ranges of 115 km may not be sufficient to account for heterogeneity in car usage, especially for long-distance trips. Hence, affected agents cannot use the car and have therefore to use other modes. Second, the time to recharge the vehicles between trips may not be sufficient to be prepared for the agents' daily schedule. Public charging may be a solution to solve this deficiency: vehicles can be charged during out-of-home trips and the charging power of public charging infrastructure is higher in general.

Figure 4 shows the trip lengths for each mode. One can also notice a shift in the trip lengths. Especially the average trip length with the mode ”car as driver” decreases, whereas the trip lengths for the modes ”car as passenger” and ”public transport” increase. The high shift towards the mode ”car as passenger” indicates that alternative modes ”walking”, ”cycling” or ”public transport” are much worse for many trips than the mode ”car as driver” regarding cost as well as accessibility and travel time. However, the carsharing modes are not affected, supposably due to the small number of overall trips.

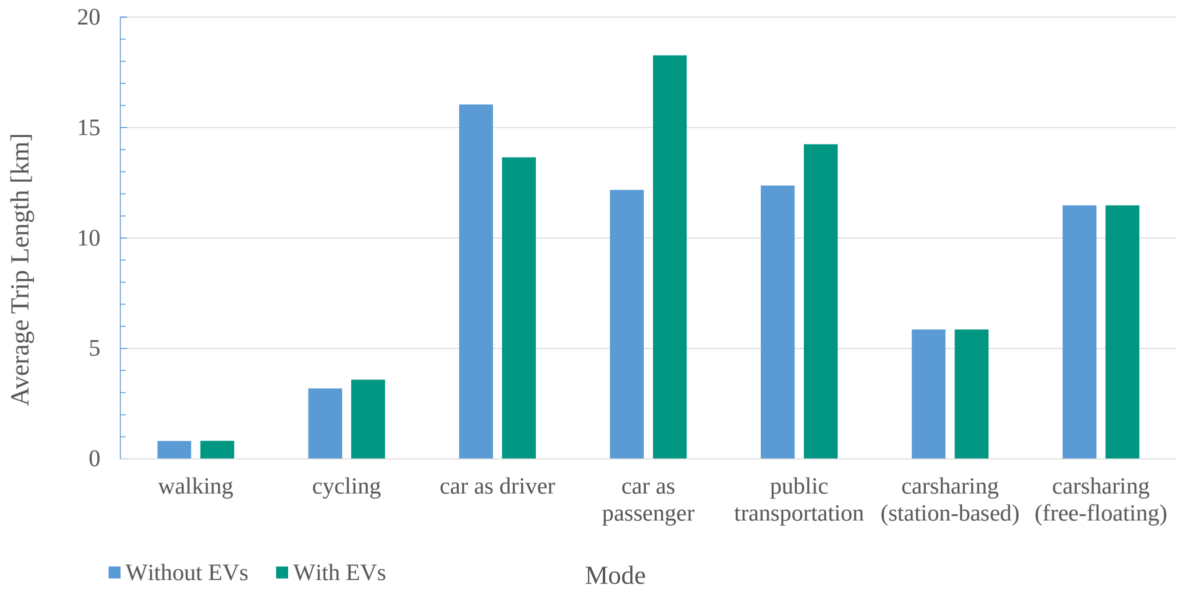

Figure 4: Average trip length by mode

6 Conclusion

Our results show that PEVs do not yet provide a sufficient range. Most people are not able to use them, considering todays range restrictions, without changing their travel behavior. We further show which modes are used instead and that the range restrictions also affect peoples destination choices. The changes in the modal split are mainly caused by the range restrictions of PEVs, which is also proven by the change in trip lengths. On the other hand, lower operational costs may diminish these effects by inducing additional car trips. However, the decreasing trip lengths are not affected by lower operational cost. Hence, low range of todays PEVs can be assumed as the restricting factor.

In future work, two issues have to be considered. First, future PEVs will have ranges of more than 200 km. This may lower the negative effects on people's travel behavior and therefore needs to be considered in the simulation. Second, and more important, supply and demand of public and semi-public charging have to be implemented in a realistic manner. On the supply side, the locations and the number of charging points at each location as well as their charging power need to be known. On the demand side, charging behavior has to be modeled correctly. Therefore, the complex interdependency of people's choice of date, type (home, semi-public or public) and location for each charging event needs to be understood and explicitly modeled.

However, the combination of the *ALADIN* and the *mobiTopp* model is a promising apporoach to account for an integrated view of user oriented purchase decisions in combination with individual travel behavior needs considering limitation of PEVs. With this approach we are able to make more precise forecasts of the usage and ownership of PEVs.

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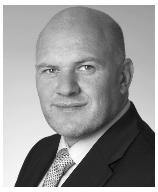

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