

Model-based estimation of private charging demand at public charging stations

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In recent years, many concepts have been developed on how to build a sufficient charging infrastructure to satisfy the demand of Battery Electric Vehicle (BEV) users. However, the focus of these approaches often lies on the spatial distribution of charging stations and the amount of charging demand is often given beforehand. In this paper, we describe a model to estimate the future private charging demand at public charging stations for different regions. Several aspects that influence the needed amount of charging stations are considered, e.g. a growing range of BEVs and the behavior of different user groups. For example, we distinguish between BEV users with or without a home charging possibility. The spatial distribution of these user groups is modeled using an agent-based approach, respecting sociodemographic properties. Forecasting the spread of BEVs strongly depends on the assumptions made regarding these influencing factors, where different current studies obtain deviant results. Therefore, in a case study for the city of Munich, we consider three different scenarios assuming a pessimistic, a realistic and an optimistic spread of BEVs in the year 2020. Additionally, we present a sensitivity analysis of the influencing factors and identify the ones that have the highest impact on the future charging demand: the overall adoption rate of BEVs is the parameter that influences the output the most. In fact, an adoption rate that is 10% higher than expected leads to an increase in charging demand of about 16%. This means, that our model strongly depends on reliable input data. The output of our model is the expected number of charging events requested in a certain region on an average day. Together with the average parking time and the temporal distribution of car arrivals at public charging stations, it is possible to obtain the necessary size of the charging infrastructure such that the demand can be satisfied even during peak hours. These results can be used as an input to existing optimization algorithms for the allocation of charging stations.

Keywords: BEVs, modeling on-street charging demand, public charging infrastructure.

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1. Introduction

In the last years, Battery Electric Vehicles (BEVs) gained in importance and came more and more to the fore of the general public. Many countries announced milestones and programs to promote electric mobility. The Federal Government of Germany, for example, set up the research program "Modellregionen Elektromobilität" to identify existing barriers for the diffusion of BEVs. One reason why many countries promote electric mobility is that BEVs are locally emission free. This fact is especially important for big cities with a lot of car traffic. These cities have serious problems with air pollution partly caused by traditional Internal Combustion Engine Vehicles (ICEVs). To make living in these cities more comfortable, the shift from ICEVs to BEVs is preferable. Additionally, many countries have ecological problems, especially when it comes to particular matter pollution (PM 10 and PM 2.5). Another reason in favor of BEVs is the fact that the stock of worldwide crude oil is finite. To diminish the dependency on oil, it is necessary to substitute ICEVs by vehicles with alternative power trains. This only makes sense if the electricity is generated from renewable energy sources. Additionally, the higher the share of renewable energies in the total energy mix, the better the overall ecological advantage of BEVs.

But there are also some advantages of ICEVs over BEVs. Firstly, BEVs are more expensive than ICEVs. For example, the electric VW Golf costs about 16% more than the comparable conventional VW Golf because of the high cost of the lithium ion battery. The battery is also a problem considering range and charging. Whereas ICEVs are able to drive up to a thousand kilometers without refueling, most BEVs have to be recharged after at most two hundred kilometers. Additionally, the refueling takes at most ten minutes whereas the charging takes from 30 minutes up to 8 hours depending on the type of charging.

To overcome these difficulties of the adoption of BEVs, research has to be done in a variety of fields. Battery and charging research is necessary to increase the range of future BEVs as well as the charging speed. Another important issue is the design of the future charging infrastructure. Where should public charging stations be built considering the future charging demand? Regarding this problem, different aspects have to be considered. Where and to which extent should charging infrastructure be offered? What would be a perfect environment for a charging station? What is the influence of the charging infrastructure on the electric grid? Which technology should be used (AC charging, DC charging)?

This paper aims to model the future number of charging events performed by private users at public charging stations on an average day. In combination with an assumption or a model about daily charging supply per charging stations, it is possible to determine the perfect size of the future charging infrastructure for private users. Afterwards, a decision maker can use an existing charging station location model to design the layout of the charging infrastructure. The focus of this estimation model lies on BEVs as these vehicles rely more on the public charging infrastructure compared to plug-in hybrid electric vehicles (PHEVs). Nevertheless, it is possible to easily adapt the model to PHEVs.

In Section 2, we present a short literature review on charging infrastructure, where we especially analyze the prediction of charging demand in the different papers. In Section 3, we explain our model to predict the future public charging demand. We state and justify our assumptions and introduce the considered influencing factors of the charging demand. In Section 4, we explain the general estimation of the input parameters of the model. This estimation is applied to real-world data in Section 5, where we conduct a case study. We choose the metropolitan area of Munich as the test site. Three different future charging demands are estimated based on three scenarios: a maximal, a median and a minimal one. Afterwards, we conduct a sensitivity analysis of the different influencing factors to analyze their impact on the amount and dispersion of public charging demand. In Section 6, we give a short conclusion of the paper as well as an outlook.

2. Literature review - charging demand modeling

There exist many approaches on how to tackle the problem of planning a public charging infrastructure. These are often set up as optimization models searching for an optimal distribution of charging stations regarding different constraints. The focus of this literature review (see Table 1) lies on the modeling of the charging demand which is considered in many of these papers. The study area is often modeled as a graph or it is divided into different regions. The optimization algorithms then decide which region or node/edge should be selected as a charging station location.

Table 1. Summary of Literature Review

Previous studies	Charging demand assumptions
Baouche et al., 2014	<ul style="list-style-type: none"> • OD matrices are considered • Consumption of BEVs is considered • Plug-in Electric Vehicle (PEV) adoption rate is a parameter
Cavadas et al., 2015	<ul style="list-style-type: none"> • Probability, that a BEV is charged at a certain location depends on the time it remains parked there • Demand can be transferred between locations • Range of BEVs and distance traveled are not considered • Time intervals with higher and lower demand are considered • No difference between people with or without a home charging probability
Chen et al., 2013	<ul style="list-style-type: none"> • Parking duration is seen as probability for charging, independent of travel distances
Dong et al., 2014	<ul style="list-style-type: none"> • Home charging considered • All cars are BEVs • Using GPS-based travel survey data
Frade et al., 2011	<ul style="list-style-type: none"> • Distinguishes between day and night demand • Day demand: number of vehicles related to jobs per region • Night demand: number of vehicles in the region • 0.33 charge-ups per day per BEV
Ghamami et al., 2014	<ul style="list-style-type: none"> • Charging demand associated with number of workers driving to work by BEVs or PHEVs • PEVs market penetration rate is considered
Lam et al., 2013	<ul style="list-style-type: none"> • Modelled by population size
He et al., 2014	<ul style="list-style-type: none"> • All cars are BEVs • Route choices of BEV users depend on available charging infrastructure
Mehar and Senouci, 2013	Modelled by <ul style="list-style-type: none"> • Traffic volume during peak hour and daily driving trip lengths • Rate of electric vehicles • Charging demand rate
Shao-yun et al., 2012	<ul style="list-style-type: none"> • OD matrix adjusted by assumed share of PEVs
Wirges and Linder, 2012	<ul style="list-style-type: none"> • Spatial and temporal diffusion of BEVs considered • Different user groups (private and business) are taken into account • Number of public charging stations estimated by consumed energy of BEVs in public • Commuter matrix between different regions considered

With the exception of Wirges and Linder (2012), demand modeling is not the focus when it comes to charging infrastructure planning. The focus lies more on the spatial distribution of charging stations than on the realistic sizing of a public charging infrastructure. Therefore, we are going to introduce a model on how to estimate private charging demand. Our model does not include an

optimization program, as our aim is not to select suitable charging station locations, but to predict the future charging demand in different regions. This demand forecast can then be used as input for a charging station allocation algorithm. Our demand model is unique in the sense that results of recent studies about BEV users are included. We consider all available information about different user groups and their charging behavior in everyday life, found out by the authors of the cited surveys.

3. Charging demand estimation model

In the present paper, we develop a model to estimate the number of daily charging events at public charging stations carried out by private BEV users. To do so, we consider a study area U which is divided into m regions r_1, \dots, r_m . As people do not only travel within the study area U , but also drive into the zone from outside, we cannot examine U as an isolated area, but need to consider the surroundings as well. Therefore, we analyze an overall study zone G composed of U and its surroundings, i.e. $U \subseteq G$. The size of G is chosen according to the average range of BEVs. We divide the overall area G into n regions r_1, \dots, r_n with the m inner regions being part of them, i.e. $m \leq n, r_1, \dots, r_m \subseteq U \subseteq G$ and $r_{m+1}, \dots, r_n \subseteq G \setminus U$. Like this, we can take both sociodemographic characteristics within and commuter movements between the regions into account. Public charging stations are defined as charging stations that are generally accessible. This means, that, for example, charging possibilities provided by companies to their employees on their premises are not public. Private BEV users are private persons who own or lease a BEV and use it for private trips. We do not consider charging demand induced by companies, e.g. by car sharing providers or haulage companies in this paper.

3.1 Assumptions:

In our model, we make some simplifying assumptions that are justified by existing studies analyzing the charging behavior of BEV owners. For example, it was observed in previous studies, that the charging behavior of private BEV owners varies depending on them having the opportunity to charge at home or not. To be more specific, in the studies by Krems et al. (2011) and Trommer (2014), BEVs were distributed to private users. In Krems et al. (2011), the authors distinguished between private users with a home charging opportunity (PWCs) and private users without a home charging opportunity (PWOCs). They found out, that PWOCs charge their BEV much more often at public charging stations than PWCs, because PWCs prefer to charge their BEV at home. This is quite reasonable, as charging at home is normally both cheaper and more comfortable. PWOCs do not have this opportunity; however, PWOCs normally use a preferred public charging station close to their home analogously to the home charging possibility of PWCs. This was observed in the same study (Krems et al., 2011), where PWOCs charged at a primary public charging station with a probability of 73%. Consequently, we assume that a high share in PWOC charging demand occurs in their home region, whereas the home charging possibility leads to no public charging demand in the home region of a PWC. In our model, we hence distinguish between the two user groups mentioned here (PWCs and PWOCs).

In the study by Trommer et al. (2013), a changing charging behavior could be observed over time. In the beginning, users recharged their BEV at almost every opportunity whereas after a short while they got used to the range of BEVs and charged less. As public charging is more expensive than home charging because of the investment and operation costs the infrastructure provider has to account for, it is assumed that BEV users only charge at public charging stations because of their personal range anxiety. Charging stations nearby their homes were stated as preferred locations for charging by PWOCs. This leads us to Assumption 1: BEV users charge at public charging stations away from their home only if they feel it is necessary because of their personal range anxiety.

Trommer et al. (2013) also found out, that BEV owners prefer to charge at private charging stations, not only at home. When going to work, for example, users charge at charging stations provided by their employer only available to the staff of the company. They do not have the time and patience to look for a public charging station when going to work during rush hour. This leads us to assuming that a trip to work is not relevant for public charging demand, as drivers will use a private charging station there or not charge at all.

In his dissertation, Badrow states, that in general most trips covered by car either start or end at home (Badrow, 2000). This means, by considering only trips starting or ending in the home region of a user, we already consider most of the undertaken trips.

All in all, the studies mentioned above lead us to assuming the following conditions:

Assumption 1. Every PWC only charges in public, if he is forced to because of his personal range anxiety. Every PWOC only charges in public in a region distinct to his home region, if he is forced to because of his personal range anxiety.

Assumption 2. Some trips are not relevant for public charging:

- a. Both PWCs and PWOCs do not charge in public if a trip ends at work, because they either have the possibility of charging their BEV at their workplace or they are not willing to search for a free public charging station every day during rush hour.
- b. PWCs do not charge in public if a trip ends at home, because they have the possibility to charge at home. This is both cheaper and more comfortable.
- c. PWOCs charge with high probability at a charging station in their home region, because they have a preferred one there.

Assumption 3. Every trip starts or ends in the home region of the user.

3.2 Definition of necessary input parameters

For the charging demand estimation model, we need some data available, as for example the number of privately owned BEVs in each region or the number of trips carried out by the citizens. Figure 1 shows a flowchart of the presented model.

The calculation of the parameter values shown in Figure 1 follows several steps. The values shown in blue circles are the data that are available from surveys or governmental data collections, i.e. Origin-Destination matrices, the share of electric vehicles in the study area (p_G), the range of BEVs (R_{BEV}), etcetera. The values in the green rectangles show the share of BEVs owned by PWCs and the share of BEVs owned by PWOCs in different regions, these values are obtained from an agent-based simulation presented in Subsection 4.1. The parameters in the orange rectangles are Origin-Destination matrices of charging relevant trips according to the assumptions presented above. Finally, the values in the purple and yellow rectangles show the probability of charging a BEV inside and outside of the home region of the owner. All of these probabilities are calculated for the two user groups, PWCs and PWOCs, separately.

In the following, all parameters needed for the model are presented in detail. For a better overview, the parameters are additionally listed in Table 2, where the abbreviations are explained. In Section 4, we explain how the values of the parameters are estimated.

First of all, let N_i be the total number of privately owned cars in region r_i . Similarly, N_i^{PWC} shall be the number of BEVs owned by persons with a home charging opportunity (PWCs) in region r_i and N_i^{PWOC} the number of BEVs owned by persons without a home charging opportunity (PWOCs) in region r_i . With these parameters, we can easily calculate the share of BEVs owned by PWCs as compared to the total number of privately owned cars in any of the regions: $p_i^{PWC} =$

$\frac{N_i^{PWC}}{N_i}$ (in region r_i). All the same, $p_i^{PWOC} = \frac{N_i^{PWOC}}{N_i}$ defines the share of BEVs owned by PWOCs as compared to the total number of privately owned cars in region r_i .

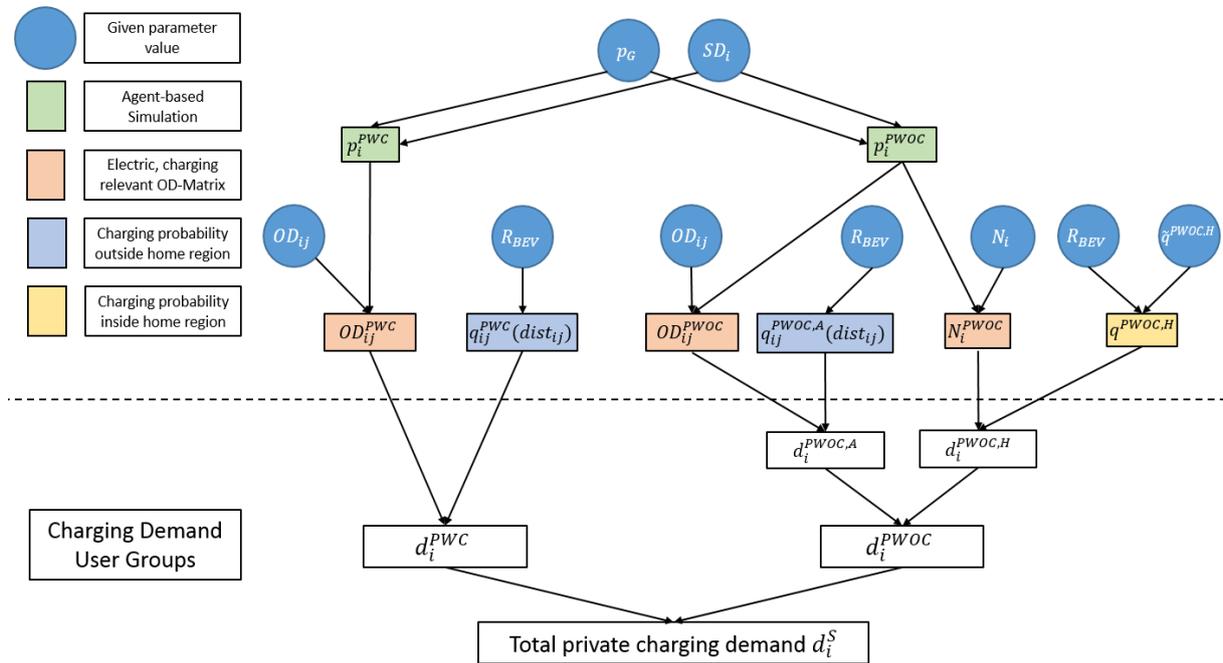


Figure 1. Flowchart of the model.

Secondly, OD^{PWC} shall be the origin-destination matrix of relevant trips for the charging model of PWCs, i.e. the entry OD_{ij}^{PWC} of the matrix shows the number of relevant trips of PWCs from the region r_i in G to the region r_j in U . Equivalently, OD^{PWOC} shall be the origin-destination matrix of model relevant trips of PWOCs, i.e. the entry OD_{ij}^{PWOC} of the matrix shows the number of relevant trips of PWOCs from the region r_i in G to the region r_j in U . As we analyze the charging demand only in the study area U and not in the overall area G , we exclusively consider trips that end within U . However, the starting point of these trips can also lie in the surrounding regions as explained above. Recall that not every trip carried out by a car owner is relevant for our charging demand model. For example, we assume that if a trip ends at the workplace of the customer, he will have the possibility to charge his car there and will not look for a public charging station (Assumption 2a). Moreover, trips with destination home are not taken into account here, as the charging probability in the home region is independent of the undertaken trips but depends only on the property, if the user is a PWC or a PWOC (Assumption 2b and 2c). All in all, the origin-destination matrices OD^{PWC} and OD^{PWOC} represent only trips that are relevant for our charging demand model.

Because of the assumptions made, the public charging probability in a region r_j other than the home region of the BEV owner only depends on the distance $dist_{ij}$ of the trip he realized to get to zone r_j ($dist_{ij}$ is calculated as the shortest path distance using the road network from the center of r_i to r_j). Let $f: \mathbb{R} \rightarrow [0,1]$ be a function matching the covered distance to the probability of charging after the respective trip. Then it is possible to derive q_{ij}^{PWC} (the probability that a PWC charges his car after driving from region $r_i \in G$ to $r_j \in U$, where r_j is not his home region) and q_{ij}^{PWOC} (the probability that a PWOC charges his car after driving from region $r_i \in G$ to $r_j \in U$, where r_j is not his home region) based on $dist_{ij}$. How the function $f: \mathbb{R} \rightarrow [0,1]$ is chosen will be explained in Section 4.

The parameter $q^{PWOC,H}$ shows the daily probability of a PWOC of charging at a public charging station in his home region. This parameter does not exist for PWCs, as they are assumed to charge at home but not at a public charging station nearby.

Table 2. Input data for our model

Input data	Possible values	Explanation
$U; G$ with $U \subseteq G$		Study Area U and overall area G consisting of U and its surroundings
$r_1, \dots, r_m; r_1, \dots, r_n$		Regions that the study area U and the overall area G are divided into: $r_1, \dots, r_m \subseteq U \subseteq G, r_{m+1}, \dots, r_n \subseteq G \setminus U, m \leq n$
N_i	$\in \mathbb{N}$	Total number of privately owned cars in region $r_i, i \in \{1, \dots, n\}$
N_i^{PWC}	$\in \mathbb{N}$	Number of BEVs belonging to PWCs in region $r_i, i \in \{1, \dots, n\}$
N_i^{PWOC}	$\in \mathbb{N}$	Number of BEVs belonging to PWOCs in region $r_i, i \in \{1, \dots, n\}$
$p_i^{PWC} = \frac{N_i^{PWC}}{N_i}$	$\in [0,1]$	Share of BEVs owned by PWCs as compared to the total number of privately owned cars in region $r_i, i \in \{1, \dots, n\}$
$p_i^{PWOC} = \frac{N_i^{PWOC}}{N_i}$	$\in [0,1]$	Share of BEVs owned by PWOCs as compared to the total number of privately owned cars in region $r_i, i \in \{1, \dots, n\}$
OD^{PWC}	$\in \mathbb{N}^{n \times m}$	Origin-Destination Matrix of relevant trips for charging of PWC (i.e. $OD_{ij}^{PWC} = \#$ of relevant trips for charging of PWCs from $r_i \in G$ to $r_j \in U$)
OD^{PWOC}	$\in \mathbb{N}^{n \times m}$	Origin-Destination Matrix of relevant trips for charging of PWOC (i.e. $OD_{ij}^{PWOC} = \#$ of relevant trips for charging of PWOC from $r_i \in G$ to $r_j \in U$)
$dist_{ij}$	$\in \mathbb{R}$	Distance from the center of the region $r_i \in G$ to the center of the region $r_j \in U, i \in \{1, \dots, n\}, j \in \{1, \dots, m\}$
$q_{ij}^{PWC} = f(dist_{ij})$	$\in [0,1]$	Probability, that PWC charges after a relevant trip for charging from region $r_i \in G$ to region $r_j \in U, i \in \{1, \dots, n\}, j \in \{1, \dots, m\}$, depends on $dist_{ij}$
$q_{ij}^{PWOC} = f(dist_{ij})$	$\in [0,1]$	Probability, that PWOC charges after a relevant trip for charging from region $r_i \in G$ to region $r_j \in U, i \in \{1, \dots, n\}, j \in \{1, \dots, m\}$, depends on $dist_{ij}$
$q^{PWOC,H}$	$\in [0,1]$	Daily charging probability of a PWOC at a public charging station in the "home" region
SD_i		Sociodemographic information about region r_i

3.3 Definition of the private charging demand at public charging stations

We now define the private charging demand at public charging stations as follows: Let d_i^S be the total number of daily charging events carried out by all private users in region r_i . This number is divided into the demand generated by PWCs and the demand generated by PWOCs. This means, we have that

$$d_i^S = d_i^{PWC} + d_i^{PWOC} \quad \forall i \in \{1, \dots, m\}, \quad (1)$$

where d_i^{PWC} is the daily public charging demand in region r_i induced by private users with home charging opportunity (PWCs) and d_i^{PWOC} is the daily public charging demand in region r_i induced by private users without home charging opportunity (PWOCs). One big difference between PWCs and PWOCs is that PWOCs generate public charging demand in their home regions, whereas PWCs have the possibility to charge at home. Therefore, we divide the public charging demand of PWOCs (d_i^{PWOC}) into the public charging demand inside ($d_i^{PWOC,H}$) and

outside of their home region ($d_i^{PWOC,A}$). This means, that altogether we get the following components of the total private charging demand at public charging stations in region r_i :

$$d_i^S = d_i^{PWC} + d_i^{PWOC,H} + d_i^{PWOC,A} \quad \forall i \in \{1, \dots, m\}. \quad (2)$$

3.4 Calculation of the private charging demand at public charging stations

We distinguish between the charging demand that occurs at public charging stations within the home region of a BEV owner, which is the case only for PWOCs, and the charging demand that occurs in other regions, which are the destinations of BEV owners (both PWCs and PWOCs) distinct from their home regions.

Let us first look at the demand occurring in the home region of PWOCs. This depends highly on the number of BEVs belonging to PWOCs in the respective region (N_i^{PWOC}). In combination with the daily charging probability $q^{PWOC,H}$ of a PWOC in his home region, we get:

$$d_i^{PWOC,H} = N_i^{PWOC} \cdot q^{PWOC,H} \quad \forall i \in \{1, \dots, m\}. \quad (3)$$

As explained in Subsection 3.2, the charging demand in a region away from the home region depends on the number of arriving trips in this particular region and the distance BEV users cover to get there.

$$\begin{aligned} d_i^{PWC} &= \sum_{k=1}^n OD_{ki}^{PWC} \cdot f^{PWC}(dist_{ki}) \\ &= \sum_{k=1}^n OD_{ki}^{PWC} \cdot q_{ki}^{PWC} \quad \forall i \in \{1, \dots, m\}, \\ d_i^{PWOC} &= \sum_{k=1}^n (OD_{ki}^{PWOC} \cdot f^{PWOC}(dist_{ki})) + d_i^{PWOC,H} \\ &= \sum_{k=1}^n (OD_{ki}^{PWOC} \cdot q_{ki}^{PWOC,A}) + d_i^{PWOC,H} \quad \forall i \in \{1, \dots, m\}. \end{aligned} \quad (4)$$

4. General parameter estimation

The design of the introduced model requires that the values of the parameters shown in Table 2 are available. In this section, we explain how these values are estimated. We are going to introduce estimation models for certain parameters and use results from existing studies.

4.1 Estimation of the spatial diffusion of BEVs (p_i^{PWC} and p_i^{PWOC})

We assume that the total share of BEVs p_G in the overall area G is given, for example by data collections of the local administration. However, from these data, we do not know the dispersion of electric mobility over the considered regions. In some regions, more people are expected to buy BEVs compared to other regions, e.g. because of differing sociodemographic attributes and transport connections in the various regions of a city or area.

One approach on how to model the electric vehicle distribution is given by McCoy and Lyons (2014). In their study, the authors describe an agent-based simulation, which assigns BEVs to agents over different time-steps. This concept can be adopted to a synthetic household population, where each household of the synthetic population is modeled as an agent. During the simulation, different characteristics are assigned to the agents based on the related household characteristics. The household characteristics are chosen due to different studies about "early adopters", i.e. about people who quickly adopt a newly presented technology (Wietschel, 2012; Campbell et al., 2012; Rasouli and Timmermans, 2013), and a survey about buyers of BEVs in Germany (Trommer, 2014).

The BEV adoption process is modeled in almost the same way as in McCoy and Lyons (2014). We will hence just briefly describe it here and refer the interested reader to the original paper. Additionally, a flow chart of the process is given in Figure 2. In the first step of the agent-based

simulation, we create a synthetic household population. This is done using the procedure presented by Müller and Axhausen (2011). Every household is seen as one agent with its respective attributes such as home region and income. In the beginning, i.e. at time step $t = 0$, none of the agents in our simulation framework owns a BEV. During the simulation, in each step more agents adopt to the BEV technology. The agent's decision to adopt to the BEV technology is affected both by its sociodemographic characteristics and by the share of BEVs in its home region, in the neighbor regions and in the overall area (see the table in Figure 2 and McCoy and Lyons, 2014). After each time step, the overall adoption and the adoption in each neighborhood is updated. Let \tilde{p}_G be the simulated total share of BEVs in the overall area. The agent-based simulation is conducted until \tilde{p}_G meets the actual total share of BEVs in the overall area (p_G), which was known beforehand. Like this, we can simulate the dispersion of BEVs over the considered regions of our overall area.

To apply the procedure, household information about the type of housing needs to be available. We assume households living in detached or semi-detached houses to be PWCs, as they generally have the room for their own private car space. The other households are assumed to be PWOCs. Like this, we can distinguish between PWC and PWOC agents, and the values of p_i^{PWC} and p_i^{PWOC} can be derived for every region.

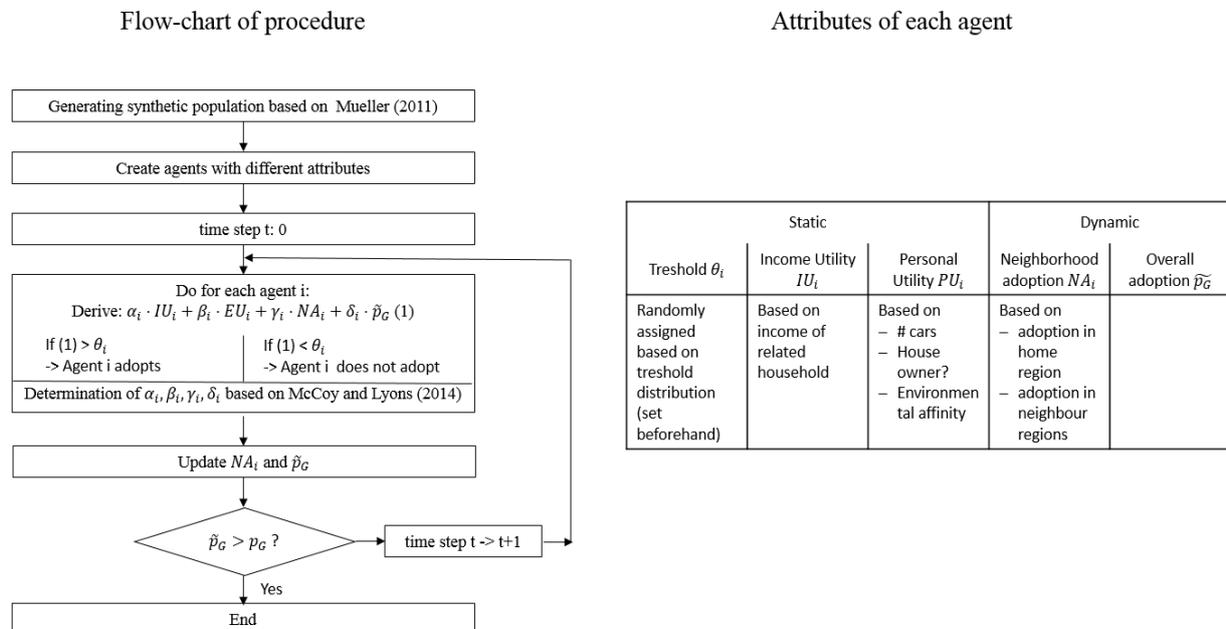


Figure 2. (a) Flow chart of simulation of agent-based BEV adoption; (b) Influencing factors on BEV adoption process for each agent.

4.2 Determination of the public charging probability after one trip for PWC and PWOC

In the following, we model the probability that a BEV owner decides to charge after a realized trip. In this model, we assume that the driver does not end his trip in his home region, as in the home region other charging probabilities apply according to the assumptions presented in Section 3. The charging probability we are analyzing here depends on the range of the BEV, the length of the trip and the personal range anxiety of the BEV user.

Let R_{BEV} be the range of a BEV and let $Y \in [0, R_{BEV}]$ be the random variable which corresponds to the number of kilometers that a BEV user is willing to drive without charging. In this model, it is assumed that Y follows a general four parameter beta distribution ($Y \sim B(p, q, a, b)$), where the parameters a and b are the bounds of the interval of the beta distribution. As a trip length is always greater than zero, it follows that $a = 0$. Furthermore, it is assumed that no BEV user tries to drive more than the remaining range of the BEV. Consequently, b is set to the remaining range.

Finally, it is possible to estimate p and q if the expected value and the variance of Y are known. The estimation of the expected value and the variance is based on the analysis of the range anxiety by Franke (2014). In his dissertation, he states that BEV users normally feel comfortable to drive a distance of 75-80% of the remaining range of their BEV. This result is based on two different surveys about BEV users (Franke et al., 2012; Franke and Krems, 2013). In these studies, BEV users were asked how far they would feel comfortable to drive with a fully charged BEV but without having the possibility to charge along the way (official range of the BEV: 165 km). The test persons were already familiar with BEVs and hence already had a feeling about the actual range. The expected value $E(Y)$ of the first study was 130 km (which equals 78% of the officially stated range) with a standard deviation $\sigma(Y)$ of 22 km (Franke et al., 2012). This means, that the ratio of the standard deviation and the expected value, i.e. $\sigma(Y)/E(Y)$, is 0.17 or, in other words, $\sigma(Y) = 0.17 \cdot E(Y)$. The authors of the second study arrived at a similar result with an expected value $E(Y)$ of about 120 km (which equals 73% of the officially stated range) and a standard deviation $\sigma(Y)$ of about 17 km, i.e. $\sigma(Y) = 0.14 \cdot E(Y)$ (Franke and Krems, 2013). In the following, we estimate the expected value $E(Y)$ to be 77% of the remaining driving range, i.e. $E(Y) = 0.77 \cdot b$ and the standard deviation as $\sigma(Y) = 0.15 \cdot E(Y)$. With these assumptions, it is possible to determine a beta distribution $B(p, q, a, b)$ based solely on the remaining range b of a BEV. This means, that the possibility that a user charges after a trip can be derived depending on the trip length (see Figure 3).

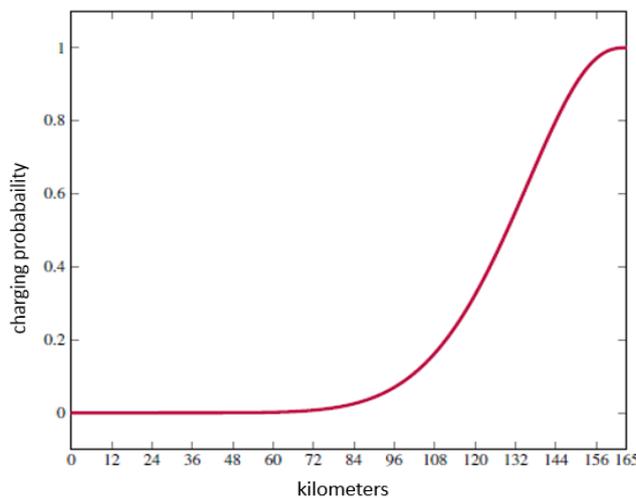


Figure 3. Charging probability depending on kilometers to drive with remaining range of 165 km.

As explained in Section 3.1, we assume that every charging relevant trip starts from the home location and the BEV is fully charged (so the remaining range b equals the maximum driving range of the BEV R_{BEV}). Furthermore, it is assumed that the BEV user drives back home after the completion of the activity. Before the start of each charging relevant trip, the BEV user has to decide if he wants to charge at his destination or not. Therefore, the charging probability depends on twice the distance of the charging relevant one-way trip.

The validity of the assumptions stated here can additionally be justified by further results of Franke et al., 2012; Franke and Krems, 2013; Krems et al., 2011. The authors examined not only the range anxiety, but also the actual charging patterns of BEV users. They found out that PWCs charge on average 2.9 times per week from which only 7% are conducted at public charging stations (Krems et al., 2011). This leads to a daily public charging possibility of 2.9%. We compared this value to the number and distances of trips per day per car derived from general travel diaries of Munich (MiD data - a national traffic survey conducted every 3-5 years; Follmer et al., 2008). The number of charging relevant trips per day per car is 0.78 and the possibility of charging after a trip is 3% assuming that $Y \sim B(p, q, 0, 165)$, $E(Y) = 130$, $\sigma(Y) = 22$ and using the

information about average trip lengths. This leads to a daily possibility of public charging of 2.3% based on the MiD data which is near the empirical results. Therefore, the assumptions of the derivation of the probability of “charging away” can be accepted.

4.3 Determination of the public charging probability of a BEV owned by a PWOC in his home region

The study of Krems et al. (2011) also analyzes the charging behavior of private BEV users without the possibility of charging their car at home (PWOCs). The authors state that PWOCs charge on average 1.6 times per week. Moreover, they figured out that about 73% of the charging events of PWOCs happened on a primary charging station. Based on these results, a daily charging rate of a PWOC BEV in its home region of $\tilde{q}^{PWOC,H} = 16.7\%$ can be derived for this study. As already mentioned, the BEVs considered in Krems et al. (2011) had a maximum range of 165 km. This means, that the daily charging probability has to be adapted according to the assumed maximum range (R_{BEV}):

$$q^{PWOC,H} = \frac{165}{R_{BEV}} \cdot \tilde{q}^{PWOC,H} . \quad (5)$$

5. Case study

In this section, we present a case study of the charging demand estimation model for Munich. It contains three scenarios, a minimal (MIN - few public charging events expected), a median (MED) and a maximal one (MAX - many public charging events expected). The goal of the case study is to depict the whole range of potential scenarios and to quantify the influence of the parameters. The minimal scenario illustrates the case that the share of BEVs does not increase eminently and BEVs are almost only bought by PWCs. The median scenario is assumed to be the realistic one based on different studies. For the maximal scenario, we assume that the share of BEVs highly increases during the next years.

Firstly, the remaining input parameters are determined from studies and empirical analyses and afterwards, the results of these scenarios are given and compared with each other. Furthermore, a sensitivity analysis of different model parameters is conducted to quantify their influence on the public charging demand.

5.1 Parameter estimation

We apply the model to the city of Munich, Germany, i.e. we choose the study area U to be the municipal area of Munich. Munich consists of 25 different city districts, such that we decide to partition the study area into 25 regions ($m = 25$). The overall area G is bounded by a cycle drawn around Munich with a radius of approximately 100 kilometers. We use our model to estimate the charging demand in the year 2020.

The overall share of BEVs (p_G) in the year 2020 is estimated in different studies (e.g. Wietschel et al., 2013; Castro et al., 2012). There are big differences between the proportions determined in the several studies ranging from 0.3% to 3.1%. For the three scenarios in this case study, we assume p_G to be 0.3% in the MIN scenario, 1.3% in the MED scenario and 2.6% in the MAX scenario. These values are based on the three different scenarios presented by Wietschel et al. (2013). To determine the share of BEVs for PWCs and PWOCs, we generate a synthetic population according to Subsection 4.1. As input data, we use a household survey (Follmer et al., 2008) and sociodemographic data of the different regions of Munich (Infas, 2012). The proportion of p_i^{PWC} and p_i^{PWOC} for each region r_i depends on the emphasis of the influencing factors of adopting the BEV technology for each agent (see Figure 2). These weights are based on McCoy and Lyons (2014) as well as on the study about BEV buyers by Trommer (2014). Obviously, the weighting of the influencing factor “house owner” is correlated to the simulated number of PWOC adopting. To be precise, if the influencing factor “house owner” is high, an agent that is not a house owner, i.e. has no possibility to charge at home, most likely does not adopt the BEV technology. This

means that there will be more PWCs than PWOCs. On the other hand, if the influencing factor “house owner” is low, it is likely that there will be more PWOCs among the group of BEV adopters. As PWOCs have to charge at public charging stations more often, a higher share of p_i^{PWOC} will lead to more public charging events. The weight of the influencing factor “house owner” is grounded on the study of Trommer (2014). For the MED scenario we choose the weight of the parameter based on Trommer’s survey, for the MIN scenario we double it (to provoke a lower share of p_G^{PWOC}) and for the MAX scenario we halve it (to provoke a higher share of p_G^{PWOC}).

01) Home → Work	06) Work → Home	11) Miscellaneous → Work
02) Home → Service	07) Service → Home	12) Work → Miscellaneous
03) Home → Shopping	08) Shopping → Home	13) Service → Service
04) Home → Leisure	09) Leisure → Home	14) Miscellaneous → Miscellaneous
05) Home → Miscellaneous	10) Miscellaneous → Home	

Figure 4. Given OD matrices differing in trip purpose.

For the three scenarios, 14 OD matrices differing in trip purpose are given (see Figure 4): As explained in the assumptions in Section 3, OD^{PWC} and OD^{PWOC} are composed of OD matrices based on the purposes of trips 3, 4 and 5, i.e. $OD = OD^{Home-Shopping} + OD^{Home-Leisure} + OD^{Home-Misc}$. We then get the matrices OD^{PWC} and OD^{PWOC} by multiplying the matrix OD by the share of the respective user group:

$$OD_{ij}^{PWC} = p_i^{PWC} \cdot OD_{ij} \quad \forall i, j \in \{1, \dots, n\},$$

$$OD_{ij}^{PWOC} = p_i^{PWOC} \cdot OD_{ij} \quad \forall i, j \in \{1, \dots, n\}.$$
(6)

To determine the charging probability after a trip (q_{ij}^{PWC} and q_{ij}^{PWOC}) or the daily PWOC charging probability at home (q_i^{PWOC}), the maximum range has to be given as explained in Section 4.3.

A study of Bloch (2014) claims a typical maximum range of about 140 km under perfect circumstances. Depending on the weather or the altitude difference of a trip, this maximum range can drop. On the other hand, it can be assumed that in the future, technical progress will go forward such that BEVs will have a higher maximum range. Based on these thoughts, for the three scenarios maximum ranges of 120 for MAX (a lower range leads to a higher charging probability), 140 for MED and 200 kilometers for MIN (a higher range leads to a lower charging probability) were chosen.

The number of cars per region of the study area N_i was provided by the city council of Munich. At the end of 2013, 497,332 private vehicles were reported in Munich (Statistik München, 2013). As it is expected that Munich will grow in the future (increase by 100,000 residents between 2009 and 2020: Prognosis by Landeshauptstadt München, 2012), a 5% increase in privately owned vehicles for the MED scenario, an 8% increase for the MAX scenario and no increase for the MIN scenario is assumed.

Table 3. Explicit assumptions for the base model

Input parameter	Scenario MIN (Minimal)	Scenario MED (Median)	Scenario MAX (Maximal)
p_G	0.3 %	1.3 %	2.6 %
Influence “house owner”	Taken from Trommer (2014) and doubled	Taken from Trommer (2014)	Taken from Trommer (2014) and halved
$OD_{ij}^{PWC}, OD_{ij}^{PWOC}$	OD-matrices bought from PTV Group (2013) and multiplied by p_i^{PWC} , p_i^{PWOC} accordingly		
N_i	497,332	522,199	547,065
R_{BEV}	200 km	140 km	120 km

In Table 3, an overview of the different parameters is given. A contradiction can be detected looking at the MAX (MIN) scenario with a short (great) range of BEVs and a high (low) adaption of BEVs. The results of the considered scenarios shall cover a corridor of the future development of private public charging demand in Munich, so the MIN and the MAX scenario are laid out as extreme scenarios.

5.2 Scenario analysis

In Figure 5, the spatial distribution of estimated charging events of the different scenarios are depicted (in the case of the MED scenario also solely for PWCs and PWOCs) as well as the overall amount of charging demand for all scenarios (also differed between PWCs and PWOCs). As we estimate the charging demand in the city of Munich, in Figure 5 you can see the 25 regions of the city, i.e. we depict the study area U and not the overall area G . It can be seen that there is a high range of the results between the minimal, the median and the maximal scenarios. This means that the future size of the charging infrastructure highly depends on the assumptions of the input parameters.

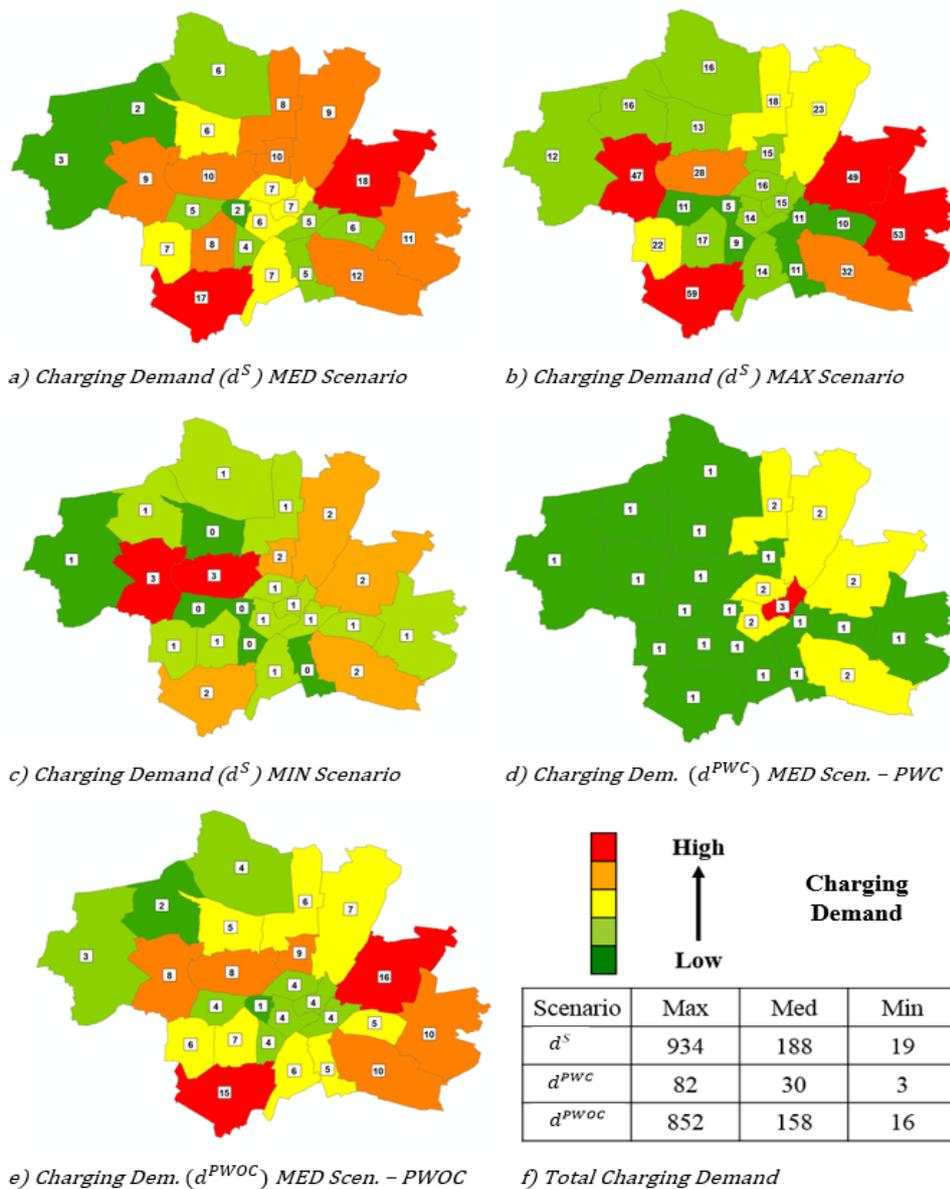


Figure 5. Results of charging demand estimation - Number of expected charging events. Shown is the study area U in our case study, i.e. the city of Munich.

While there are big differences in the number of charging events of the three scenarios in the whole Munich area (see Figure 5f), there are almost no differences regarding the relative spatial distribution of the charging demand over Munich. In Figure 5a, you can see the spatial distribution of the total public charging demand assuming the median scenario. The spatial distribution of the demand looks similar for the maximum (see Figure 5b) and the minimum scenario (see Figure 5c), which means that the total number of charging events differs but not the relative size of the demand in each region. The highest charging demand occurs in the southwest and in the northeast of Munich, whereas in the northwest less public charging events are expected. Furthermore, the results show that most of the charging events are executed by PWOCs (see Figure 5f). Moreover, the spatial distribution differs between the two user groups. PWOCs charge more often near the city center of Munich (see Figure 5d), whereas PWOCs are also dependent on a public charging infrastructure in the outer parts of Munich (see Figure 5e).

Because of the high deviations in charging demand estimation based on differing assumptions, it is hard for decision makers to plan a public charging infrastructure that is suitable for future demand. Infrastructure planners should be aware of potential changes in reality compared to their assumptions. Before setting up an infrastructure plan, they should know the impacts of each input parameter to be able to adapt their plan whenever changes occur. Therefore, in a next step, we analyze the input parameters in more detail conducting a sensitivity analysis.

5.3 Results of the sensitivity analysis

In this section, we analyze the influencing factors “Overall BEV Adoption”, “PWOC BEV Adoption” and “Range of BEVs” in more detail. Each of the four input parameters is slightly changed within the range of 90% to 110% of the corresponding value that we expect in the median scenario. The result of this analysis is depicted in Figure 6.

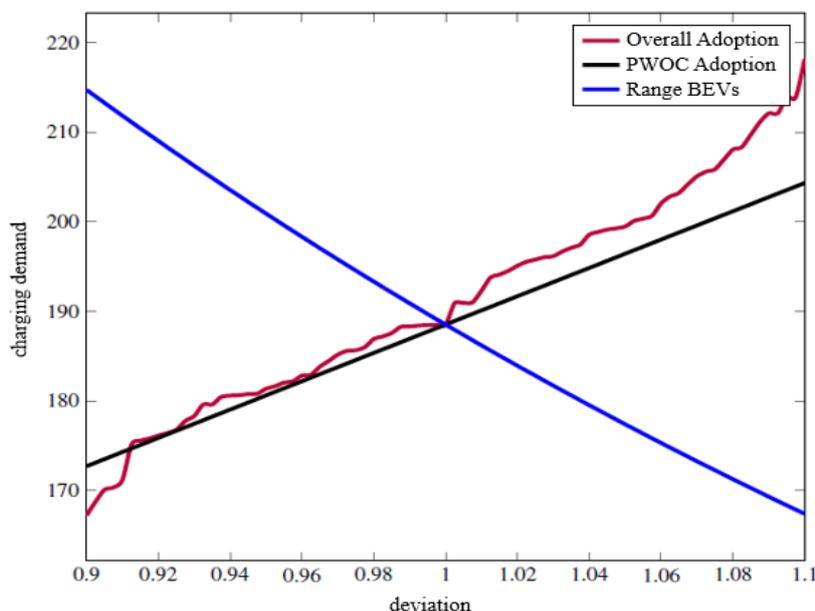


Figure 6. Sensitivity analysis of different influencing factors of public charging demand. The charging demand is measured as the number of private charging events at public charging stations in Munich per day.

Small changes in the overall adoption p_G influence the public charging demand the most. A BEV adoption that is 10% higher than expected leads to an increase in the number of charging events of about 16%. We can see in Figure 6 (red curve), that the charging demand increases much more if the deviation is higher. This is due to the fact that, if the adoption rate is high, PWOCs are also more likely to adopt to BEVs and PWOCs generate a higher charging demand. The black curve

shows the influence of the number of PWOCs buying a BEV. This curve is almost linear with a slope of almost one, such that a 10% increase in the number of PWOCs results in almost a 10% increase in the number of charging events. As expected, the sensitivity of the charging demand is inverse to the influencing factor "Range of BEVs" (blue curve), because a higher range of the BEV leads to less charging events that need to be carried out. As the range is expected to grow more than 10% in the near future (Bosch GmbH, 2015), less charging events per BEV will be executed.

6. Summary and outlook

In the beginning of the paper, we presented a literature review introducing the most important papers that deal with the planning of the future charging infrastructure. However, as most papers focus on the optimal allocation of charging stations, there is not much literature about estimating the future charging demand. Therefore, we introduced a new model considering different BEV user groups (PWCs and PWOCs), the future adoption of electric mobility respecting sociodemographic characteristics, the evolution of the range of BEVs and general traveling patterns. In a case study for Munich we applied the presented model assuming three different scenarios regarding the spread of BEVs.

The output of the model is the expected number of charging events requested in a certain region on an average day. Together with the average parking time and the temporal distribution of car arrivals at public charging stations, it is possible to obtain the necessary size of the charging infrastructure such that the demand can be satisfied even during peak hours. Together with existing optimization algorithms for the allocation of charging stations, our model can help planners to design a reasonable and capable charging infrastructure, if reliable data for setting the parameters are given.

As the results differed a lot between the three scenarios, a sensitivity analysis was conducted to detect the influence of each parameter. We found out, that the estimation of charging demand is not robust, i.e. it heavily depends on the quality of the input - mainly on the future share of BEVs. This dependency on correct input data is the main limitation of the model, as the future spread of BEVs is very difficult to predict and a wrong forecast leads to an incorrectly estimated charging demand. Therefore, it is necessary to consider small planning horizons to be able to adapt the model to changing situations. It is also important to monitor the utilization of existing infrastructure to identify misconceptions and avoid mistakes. However, the spatial distribution of the determined charging demand does not depend on a certain scenario. Therefore, if the planning horizon is bigger and data hence less reliable, our model can at least be applied for estimating the relative spatial distribution of the public charging demand.

It is also possible to include other parameters into the model, like for example congestion. We consider the results of different studies saying that people feel comfortable to drive about 77% of the remaining range without charging. This means, people intuitively leave some kind of buffer for possible congestion and detours. However, if more emphasis should be put on congestion, it is possible to define the distance $dist_{ij}$ between regions r_i and r_j considering the average congestion on this way. It is even possible to define the distance dynamically depending on the time the trip is done, yet this assumes that drivers are aware of the traffic situation on their trip and plan their charging events accordingly. Additionally, it is possible to apply the presented model to other cities. However, one must be careful as trip and charging behavior as well as the influence of sociodemographic attributes on the adoption of BEVs might be different in other regions of the world. The assumptions made in this paper are based on studies about mobility, the adoption of BEVs, and charging behavior in Germany. Therefore, the assumptions made here would need to be checked and, if necessary, adjusted for the respective region.

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