COMPUTING SPATIAL CHARGING NEEDS USING AN AGENT-BASED DEMAND MODEL

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ABSTRACT

The buildup of electromobility necessitates strategies for deploying charging stations that match demand and allocate them in space. This paper presents a fine-grained approach for determining the charging needs and allocating the according charging infrastructure using the results of an agent-based traffic demand model. The usage of a fine-grained representation of each individual's daily trips delivers both driven distances and stay times at activity locations which are, respectively, used to compute the consumed energy and the times available for recharging. Based on these data, charging points are then allocated. An example of applying this method to the city of Berlin is presented.

INTRODUCTION

Traffic is responsible for around 20% of green house gas emissions in Germany (UBA 2012). Motivations for reducing the environmental impact of petroleum-based traffic come from different directions. Global climate change can only be stopped if less green house gases are emitted. Local administrations in Europe cope with the air quality regulations formulated in the "Directive 2008/50/EC on ambient air quality and cleaner air for Europe" (EP 2008) which limits the concentrations of air pollutants that affect the environment and the population's health. Finally, peak-oil is a long-discussed issue.
One of the currently pursued solutions is the encouragement of electromobility, which, if using renewable resources for generating electricity, could reduce traffic's impacts by decreasing both climate change and the pollution of the environment.
Besides developing these vehicles, proper strategies for deploying the necessary charging infrastructure are required. Not only the amount of the required charging stations has to be determined, but also the locations they should be positioned at. The lack of appropriate public charging infrastructure is identified as one major challenge when transiting to a system of electric mobility (Trommer et. al. 2015).
The computation of the needed infrastructure as well as its allocation in space has been addressed by research in the past years. Anderson et. al. determine the loading needs for one million electric vehicles envisioned by German government for the year 2020 using vehicle usage data from the MiD 2008 mobility survey (Anderson et. al. 2016), yet neglecting the allocation in space. Some approaches allocate charging infrastructure in space using road usage (Ip et. al. 2010) or by weighting activity locations (Gkatzoflias et. al. 2016). But one may as well find other approaches that evaluate single vehicle rides as done in the following. They use either data collected from the real world (Dong et. al. 2014) or ones generated by demand models (Xi et. al. 2013). Some approaches apply an optimization scheme for computing the best placement of a limited number of charging stations (Xi et. al. 2013, Dong et. al. 2014). Other investigate the relationship between charged vehicles and the energy grid (He et. al. 2013, Loisel et. al. 2014).
The remainder is structured as following. First, a short introduction into the used traffic demand and the used simulation settings are given. Then, the procedure of computing the charging demand is described. Afterwards, the computed charging needs are presented and discussed. Finally, the conclusions are given.

USED MODELS AND SETTINGS

In the following, the agent-based demand model used, TAPAS, is outlined first. Then, the representation of the region used for computing the charging needs and allocating the charging infrastructure is discussed.

Introduction to the demand model TAPAS

The presented investigations use the agent-based demand model "TAPAS" (Heinrichs et al. 2016). TAPAS uses a representation of a region's population where every person is modelled individually and is described by a set of socio-demographic attributes, such as his/her age, sex, employment status and information about the availability of mobility options (i.e., driving license, public transport season ticket, bicycle). Each person belongs to a household which has additional information about the available cars and the household's monthly income. Every household is located at a certain geo-location within the modelled region.
A region as represented in TAPAS consists additionally of the locations of activities, such as work places, schools,

shops, or recreation places, and matrices that resemble access, egress, travel times and costs for the regarded modes. TAPAS models the modes "walking," "bicycling," "car driver," "car passenger," "public transport," and "car sharing."

TAPAS processes the modelled population by iterating over households, first, then over the persons. For each person, a daily activity plan obtained from the German mobility survey "Mobilität in Deutschland 2008" ("MiD 2008"; Infras & DLR 2010) is chosen. Then, TAPAS computes the locations at which the activities take place as well as the mode of transport used to reach these locations. The daily activity plans are hierarchical; if, for example a trip chain contains the trip to work, approaching the work place is computed first. Additional actions, such as shopping performed on the way to or from work what is the main activity in this example, are computed afterwards. If the resulting trip chain extends given time limits or costs, it will be dismissed and a new plan is computed. Figure 1 shows the workflow of the TAPAS demand model.

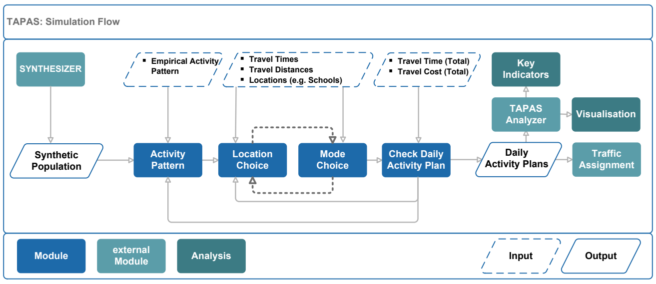

Figure 1: TAPAS workflow.

The used travel mode is determined using a multinomial logit model which is obtained by a regression of the mode choice options from the MiD 2008 survey against the attributes of persons, households, and the trip (chain). The locations are chosen either using a gravity-based (Hua and Porell 1979) approach or using so-called intervening opportunities (Stoufer 1940).

TAPAS delivers for each modelled person the trip chain for a complete average working day. This trip chain consists of single trips which are described by the departure and arrival places, times, the travel time, the used mode of transport, etc. A large set of evaluation tools can be employed to aggregate these result for obtaining, e.g., the information about certain user groups' behavior or the population's responses to regulatory, fiscal, infrastructural, or political measures (Krajzewicz et al. 2016). The generated trip chains can as well be further processed by the open source microscopic traffic flow simulation SUMO (Krajzewicz et al. 2012) for obtaining a user assignment, traffic flow measures, or pollution amounts.

To simulate electromobility, the representation of vehicles within TAPAS was extended by a maximum range. If the sum of the way length performed by an electric vehicle extends this range, the according plan is marked as being infeasible and is thereby dismissed.

The region of Berlin

In the following, a simulation setting that resembles the traffic demand in the city of Berlin in the year 2010 is used. Summarized information about the region is presented in Table 1. The population, including the persons and the households, was generated by applying the Iterated Proportional Fitting and the Iterated Proportional Updating algorithms to match data from Zensus 2011 and Mikro-Zensus 2011 (von Schmid et. al. 2016). The information about dwellings in Berlin used as input for the origins was supplied by the administration of Berlin and describes June 2012. Different data sources were used to model activity locations, including the NEXIGA data set which describes the year 2012 as well as OpenStreetMap data and other sources.

Table 1: Basic statistics of the simulated region.

Number of persons	3,287,530
Number of households	1,904,569
Number of vehicles	1,049,604
Number of dwellings	546,672
Number of Activity locations	351,289

The availability of driving licenses per age and sex and the car ownership per household are given in Figure 2.

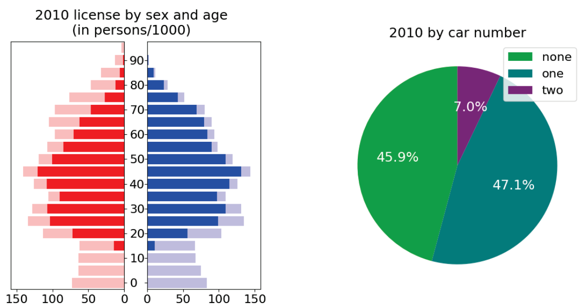

Figure 2: left: distribution of driving licenses per age and sex; right: car ownership per household.

The motorization rate in terms of vehicles per square kilometer and the modal split computed by the plain, as-is simulation of the region are shown in Figure 3. In the following, only rides performed by the motorized individual traffic mode ("driving a car") will be considered.

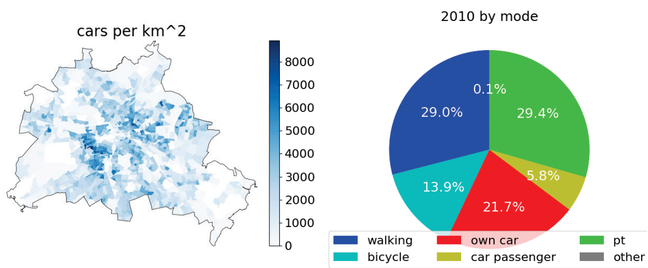

Figure 3: left: numbers of vehicle per square kilometer; right: the computed modal split.

CHARGING DEMAND

Electromobility and daily vehicle use

It should be noted, that neither the reduced price of using electric vehicles nor their lower range when compared to conventional vehicles are regarded in the following. This is motivated by an initial evaluation of distances covered by single trips and daily activities. As shown in Figure 4, 100% of single trips can be covered using the currently available ranges of electric vehicles of 150km and this even holds when taking a maximum range of 100km. As well, this is even the case for complete daily usage of vehicles as about 99.9% of distances traveled over a complete day can be covered without recharging. Please note that no commuting routes coming from regions beyond the modelled ones are considered in the given TAPAS settings. The solid lines in Figure 4 show the current common ranges of electrical vehicles of 100km and 150km. The dashed lines represent common distances driven by electric vehicle users as reported in (Frenzel et al. 2015, see Trommer et al. 2015 for a reduced English version) for reference.

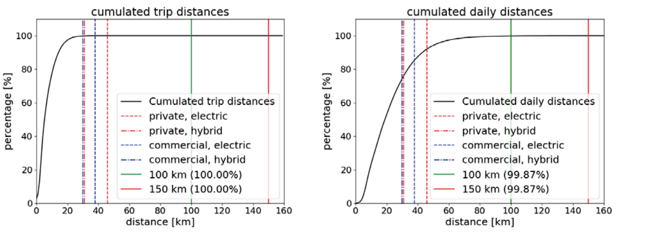

Figure 4: Cumulated distances of single trips (left) and complete daily car usage (right).

To summarize, one should assume that electromobility, given currently available ranges, can be employed in the regarded urban region without limiting mobility needs.

For simulating the maximum-fall, which in fact matches the envisioned plans for introducing electromobility (Zimmer et al. 2016), a 100% penetration rate of electric vehicles is used in the following evaluations.

Models for energy consumption and recharging times

It is assumed that a portion of the vehicle fleet is parked at privately owned places, such as a garage or a car port, and can thereby be charged at home. Socio-demographic, socio-economic and infrastructure data as well as data on the type of building at the level of a sub-traffic assignment zone ("TVZ – Teilverkehrszelle") have been used to compute the probability of a vehicle being charged at home using a linear regression. The resulting probabilities are shown in Figure 5.

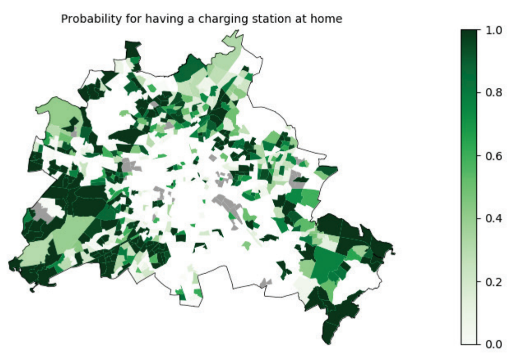

Figure 5: Probability for having a charging place at home (grey: missing values).

Still following the assumption that most of the daily trips can be completed without a recharge, the so determined 309,528 of overall 1,049,604 vehicles that can be recharged at home are disregarded in the following determination of the needed charging infrastructure. Vehicles within the 67 of 1223 zones that do not have a probability of home charging infrastructure supplied (shown grey in Figure 5) were assumed to have no loading infrastructure.

The energy consumption of the vehicles is not modelled explicitly. Rather, the amount of driven distance(s) is put against the recharging speed, which, itself, is computed as (re-)gaining a range within a given time span. The recharging speed is taken from (Hardinghaus et al. 2016). The respectively obtained recharging times for (re-)gaining a range of 1km are 5 minutes when using the slow (AC) and 1 minute when using the fast (DC) technology. One may note that these values are the measured plugged-in times, which include the time already completely recharged vehicles stay connected to the charging station. Theoretically, the AC technology should be capable to regain a single kilometer within 2 minutes and DC within 1/7min.

The recharging model assumes that at least 15 minutes are needed for recharging. All halts below this value are not used for recharging. From all halts above this duration, 15 minutes are subtracted to obtain the remaining charging time.

NEEDED CHARGING CAPACITIES

As motivated above, the charging needs and places for allocating the required infrastructure are determined by executing the model and evaluating the computed trip chains performed by car drivers. In the following, the traveled distances are put against the respectively following halting times to show that the energy lost during a trip can often be not recharged at the destination, first. Then, the method for allocating the needed charging infrastructure is described.

Energy consumption and recharging times

When looking at the relationship between traveled distances and the subsequent stays, as shown in Figure 6, one may note that the stop time is often not sufficient for recharging the energy that was used to approach the respective destination. This applies to both the slow AC and the fast DC technology.

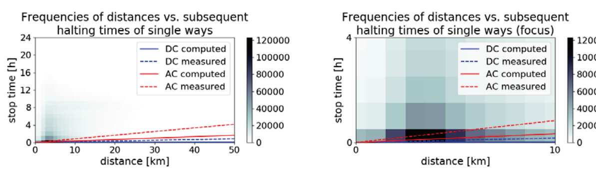

Figure 6: Occurrence distribution of driven distances vs. the subsequent halting time; left: all measurements, right: focus on small distances and travel times.

Charging needs allocation

For determining the charging needs, the trips performed by car are aggregated at their destinations. In a first step, vehicles are recharged using the slow AC technology at their destinations if their stop times allow to completely recharge them. The resulting amount of needed charging capacities is given in Figure 7, distinguishing between different types of subsequent activities.

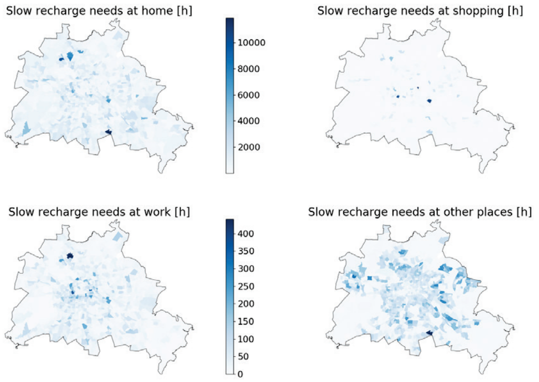

Figure 7: Needed slow (AC) charging capacities per TVZ; from left to right, bottom to top: at home, shopping, work, other.

Still, only a portion of the charging needs can be solved using the slow recharging AC technology. Vehicles that cannot be recharged using AC during the stay duration are assumed to recharge using the faster DC technology. Figure 8 shows the resulting DC capacity needs.

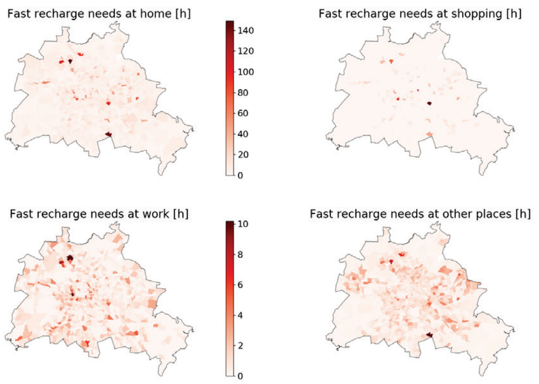

Figure 8: Needed fast (DC) charging capacities per TVZ; from left to right, bottom to top: at home, shopping, work, other.

The summarized needed recharging capacity is given in Figure 9 for the slow charging mode (AC) and in Figure 10 for the fast charging mode (DC).

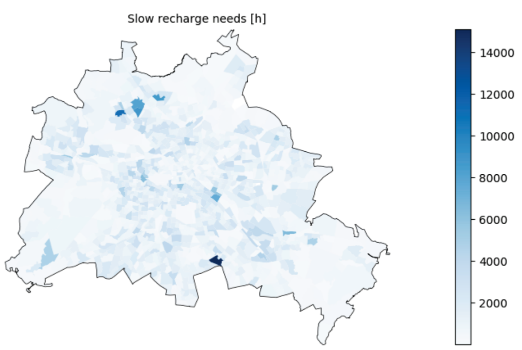

Figure 9: Needed slow charging (AC) capacities per TVZ.

Naturally, the distribution of the charging times correlate with the halting times and the distances traveled to reach the respective activity. Within the spatial distributions in Berlin, an area in the south shows to be a prominent one for all types of activities but work. This area is the "Gropiusstadt" – a dense populated area with Berlin's biggest shopping mall.

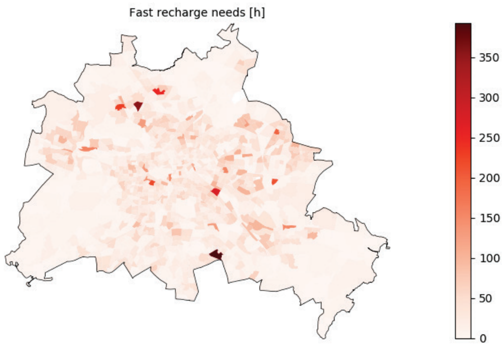

Figure 10: Needed fast (DC) charging capacities per TVZ.

Finally, the charging needs normalized by the area are given in Figure 11.

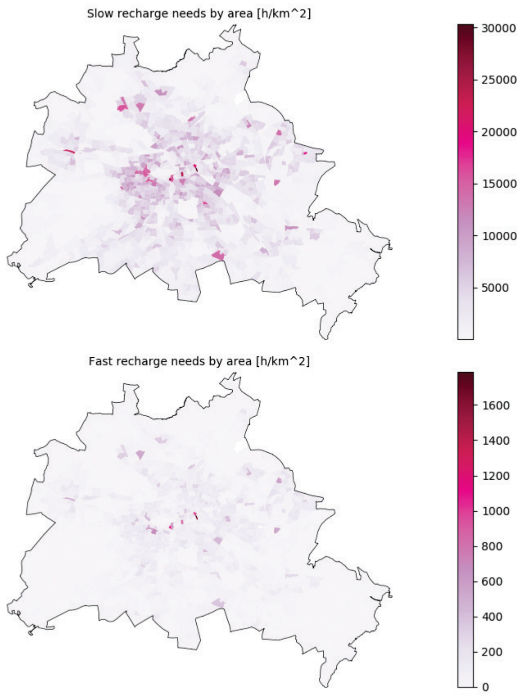

Figure 11: Needed slow (AC, top) and fast (DC, bottom) charging capacities per square kilometer per TVZ.

CONCLUSION

A method for computing the needs for recharging electric vehicles and for allocating the according infrastructure is presented. The method uses the results of the agent-based traffic demand simulation TAPAS which delivers for each modelled individual the trips performed during a usual working day.

Initially performed evaluations show that the ranges of current electric vehicles are sufficient for all single trips and for almost all distances covered during the complete day within the used Berlin test-case yet ignoring commuters. In contrary, if halts at home are neglected, many activities performed during the day are too short to regain the energy lost while approaching them.

Using the fine-grained results of the demand model, an allocation of charging needs at the level of traffic assignment zones could be determined. For this purpose, distances driven before accessing a destination were summed if the time the vehicle remains at the destination is sufficient for being completely recharged. The results show that in specific areas, a very high density of charging points is needed which one may assume to be hardly achievable.

Different extensions to the proposed methods should be performed in the future. First, the demand model should be extended by commuter trips from and to regions outside Berlin and the yet neglected changes in behavior when using electric vehicles should be investigated more deeply. Then, the available interfaces to a traffic flow simulation could be used for increasing the quality of the model for energy consumption. As well, the assumed threshold of 15 minutes below which a vehicle is not recharged should be discussed and revisited.

In addition, the resolution of placing the charging stations could be increased taking into account the given road and parking infrastructure at the TVZ. Finally, the given method computes the charging needs over a complete day. For delivering the number of needed charging stations, one should allocate recharging in time and design methods for scheduling recharging over the day.

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