Simulation of Daily Charging Needs in Ulm / Neu-Ulm

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Abstract

The share of electric vehicles is planned to increase to more than 90% in the year 2045. Consequently, the capacity of the energy grid must be accordingly extended. For predicting future loading needs in the cities of Ulm / Neu-Ulm (Germany) and projecting them onto the existing energy grid, a tool chain has been realized, described herein. The resulting simulation system computes the charging needs and interactions between the grid and the vehicle fleet on a disaggregated level of single vehicles, their stops – locations and durations –, and single lines from the cities' energy grid. The results shall help the organization responsible for the energy grid to plan necessary extensions.

1 Introduction

The project InterBDL works on the realization of bi-directional charging addressing mainly the interoperability between involved elements and systems as well as regulative and legal issues. Bidirectional charging or vehicle-to-grid technology (V2G) promises to contribute to the resilience of the energy grid by offering a large battery capacity for storing unconsumed energy and giving it back to the grid when needed. Besides, this technology enables owners of electric vehicles to trade energy. In either case, the electrical grid's capacity has to be increased to accommodate the additional load. As such, a work item of the project is to predict the additional demand – including both, retrieving and storing energy – put on the energy grid by a higher share of electric vehicles to be expected in the future.

Much of the academic work focusses on the allocation of new charging stations. Different methods for predicting the charging needs have been used for this purpose, see e.g. [1] for an overview. So-called agent-based demand models (ABMs) that replicate the mobility of the population are currently assumed to be the best choice [2] for this purpose. The work presented herein employs an established ABM named TAPAS [3] and extends the obtained mobility patterns of the population by heavy-duty vehicle trips extracted from a commercial dataset. As ABMs model the behavior of single persons, they deliver a representation of mobility that is disaggregated both on the spatial as well as on the time scale. The obtained interactions are projected onto a representation of the real-world energy grid within the regarded area of the cities Ulm / Neu-Ulm.

Following the long-term planning needs of grid suppliers, the investigation looks at future shares of electric vehicles, namely the year 2045. The German project Ariadne [4] assumes – in dependence to the scenario – a share of electric vehicles of about 25% for the year 2030 and about 90% to 95% for the year 2045. This is in-line with the predictions given by the network operators [5], being between 40% und 70% in the year 2037 and raising to 70% to 95% in 2045.

The remainder is structured as following. In the next section, the used models and the data processing pipeline are presented, first. Afterwards, in section 3, the results of applying it are shown. Section 4 gives the conclusions, discussing the results and the benefits and shortcomings of the used pipeline.

2. Methodology

The prediction of the additionally needed capacity in the cities Ulm / Neu-Ulm posed by a full electric vehicle fleet is computed using a chain of different models. In a first step, the agent-based demand model TAPAS is used for determining the daily activity patterns of the cities' populations. The resulting trip chains are then filtered for obtaining trips performed using a private vehicle, which are then mapped onto parking places assigned to the trips' destinations. In addition, a data set from INRIX is used to replicate the charging needs of heavy-duty vehicles used for commercial transport. Subsequently, charging decisions are simulated using the model CHARGIN [6]. The obtained information about interacting with the grid is mapped onto the representation of the energy grid of the regarded area. The involved models and the process of mapping the demand onto the grid are described in a higher detail in the following subsections. The overall workflow is depicted in Fig. 1.

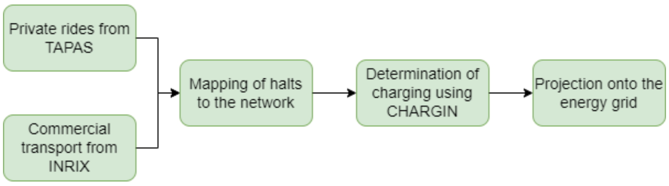

Fig. 1 The overall workflow of modelling future charging load

2.1 TAPAS

TAPAS is an agent-based demand model (ABM) that computes the daily mobility patterns for a given, disaggregated synthetic population of a region under investigation. For each modelled person, TAPAS selects a matching daily mobility plan from a set of about 50,000 empirical day plans using a probability distribution that gets the respective person's socio-demographic attributes as input. The plan consists of the activities performed during a usual working day. For the selected plan, the places at which the activities can be performed are selected first, together with the mode(s) of transport used to access them. The results of a TAPAS run consist of a list of the trips performed by each simulated individual during a usual working day. Each trip is described by information such as the starting and ending locations, the departure time and the duration of the trip, as well as the chosen mode of transport.

Besides a representation of the population, disaggregated into single persons and households, TAPAS needs the information about the activity places as well as matrices that describe the performance of the regarded modes of transport – walking, using a bike, motorized individual transport as a driver or a co-driver, and public transport. Collecting all the needed information has been a time-consuming and partially expensive process in the past. Available data sources had to be collected, converted, and aligned, and often, commercial data that covers working locations and their capacities had to be bought. To omit these issues, a tool was built within the project that automatically collects data from sources that cover the complete area of Germany and converts them for being used in TAPAS [7].

Given this tool, the region around the cities of Ulm / Neu-Ulm was prepared as input for TAPAS. While the population was modelled for the area covered by the cities, activity locations were generated for a bigger region, allowing the population to visit locations outside of the cities as well. Fig. 2 shows the modelled region. Overall, the simulation covers a population of 275,543 individuals grouped into 136,786 households, and 171,268 private vehicles.

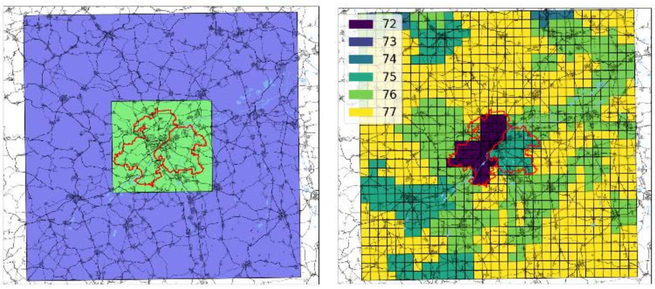

Fig. 2 Left: the modelled area, distinguishing the one for which the population has been modelled (green) and a surrounding area with additional activity places (blue); right: the division of the area into Regiostar 7 classes

The obtained simulation was calibrated using the trip distance distributions obtained from the national survey "Mobilität in Deutschland 2017" (MiD, [8]), segregating the modelled area into so-called traffic analysis zones, which were assigned to their respective Regiostar 7 region class. In a second step, the resulting mode choice was validated, again using data from the MiD. The results of the mode choice calibration for the Regiostar 7 class 72 are given in Fig. 3.

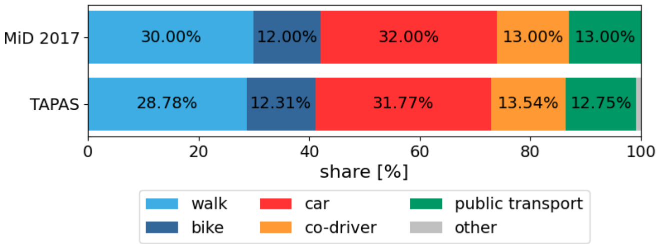

Fig. 3 Comparison of the modal split from the MiD survey against the one obtained from TAPAS

The 275,543 modelled persons perform 3.8 trips per day on average. The major activities performed during a usual day (see also Fig. 4) are working (28%), leisure activities (24%), shopping (19%), and errands (17%).

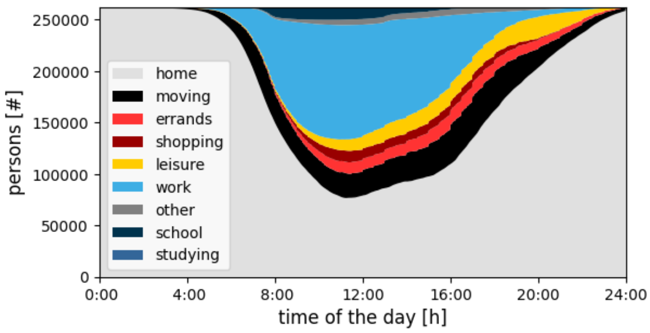

Fig. 4 The activities performed by the population of the modelled area as delivered by TAPAS

The trip chain information generated by TAPAS for each inhabitant of the region is mapped onto the halting positions (see 2.3) and further processed by CHARGIN for obtaining the charging load (see 2.4).

2.2 Commercial Transport

For including commercial transport in the forecast, an external dataset was used. This dataset contains the information about 255,000 stops of heavy-duty vehicle in segments N2 and N3 within the considered region for the month March 2024. Each data point names the vehicle type, as well as the assumed distance driven before halting. The information about the dwell time is given for about 50% of the described halts. Fig. 5 shows a heat map generated using this data.

As done for the trips obtained from TAPAS, the reported stops of commercial rides were mapped onto the existing parking places (see 2.3). For obtaining a data set that matches the one generated by TAPAS, only halts during Tuesday, the 12th of March 2024 were selected.

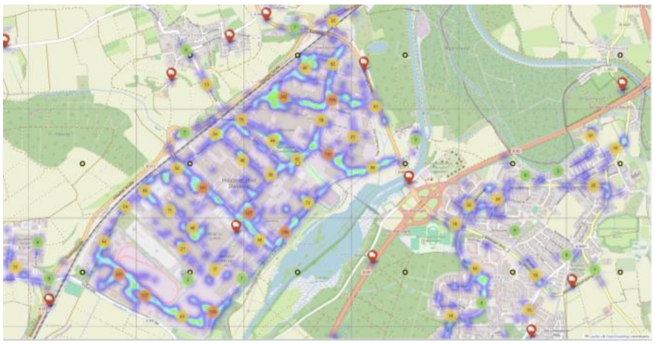

Fig. 5 Heat map of halting positions of commercial vehicles in Ulm/Neu-Ulm.

In addition, a linear regression was used to predict the development of the electrification of commercial fleets based on data from the German Federal Motor Transport Authority [9] and predictions about the development of the private vehicle fleet following the "T-45 Strom" scenario from [10]. Table 1 shows the results for different vehicle segments of commercial vehicles.

Table 1: Assumed development of the electrification of commercial fleets by vehicle segment

Vehicle Segment	2024	2035	2045
N1	2.5%	93%	100%
N2	0.5%	67%	98%
N3/SZM	0.05%	53%	95%
M3	2.5%	75%	100%

2.3 Determining Halting Positions

When reporting performed trips, TAPAS stores the locations each trip starts and ends at. For projecting the destinations onto the electricity grid, the respective parking positions must be determined, first. As such, parking possibilities – both parking places and on-street parking areas – were extracted from OSM. For each activity place, the parking possibilities within a radius of 500 m were then determined. In the given variation, the parking place with the highest capacity to distance ratio is selected for a regarded destination. This assignment can yet be changed for replicating different parking choice patterns, what has not been done, yet. The result is a mapping of the rides performed by motorized individual transport onto the parking infrastructure. The stops given in the INRIX dataset for commercial vehicles were mapped onto the parking infrastructure as well. Here, the nearest halt was selected.

2.4 CHARGIN

CHARGIN is a microscopic (vehicle-based) model of charging behavior. It obtains the diaries of vehicles, including the driven distances as well as stops, their durations and the activity performed by the driver during the respective halt. CHARGIN uses data derived from a survey among users of electric vehicles [11] to replicate the according probabilities to charge. Additional information needed consists of the available charging power and the charging price at the stop. The vehicle's state-of-charge is computed by the model using the information about the distances driven since the last charging. CHARGIN relies on two assumptions: 1) that the users of vehicles behave like the ones of combustion-engine vehicles, meaning that the daily mobility patterns do not change, and 2) that charging takes place at the locations the vehicles are parked at. On-trip charging is assumed to be used only if the state-of-charge falls below a certain threshold.

The model delivers single charging actions with a time resolution of one hour for the course of a complete week. The driving patterns are either generated from surveys like the MiD or by models like TAPAS as presented herein. In case of using TAPAS results, which model a single day only, the given day is repeated to obtain the weekly driving patterns. The output distinguishes between single vehicles and charging points, allowing for according disaggregated evaluations.

In the scope of the project, CHARGIN is extended for replicating bi-directional charging behavior. Currently, the following assumptions are made: 1) the vehicle is charged, first, for assuring spontaneous mobility, being set to 100 km range, 2) a halting time of at least 15 minutes is necessary to start charging, 3) for bi-directional charging, the halting time must be above 60 minutes.

2.5 Mapping on the Electricity Grid

The project partner Stadtwerke Ulm/Neu-Ulm Netze GmbH supplied a representation of the energy grid as geo-data. The energy grid consists of low and medium voltage lines, both being either underground or overhead lines. Additional data includes the information about connections along the single lines and connections to the transformers. For each parking place, the nearest part of the energy grid was determined distinguishing between low and medium voltage lines. The information about connections to the transformers was used to aggregate the charging needs from being mapped to single halting positions to bigger spatial areas in the wish to reduce the stochastic effects of the involved models (see also 3. Results). Two spatial aggregations were considered: one at the level of switching cells, and one that aggregates these areas at the level of transformers.

For each parking possibility, the respective next line of the low and medium grid was determined. This information is used to map the charging demand of electric vehicles to the respective part of the energy grid, considering the aggregation levels given above.

3 Results

In the following, preliminary results are presented. The involved models are stochastic in nature and, while delivering valid aggregated results for an area under investigation, they are not capable to exactly represent an existing, real person. As such, the simulation of the current number of electric vehicles would deliver results that differ from the reality mainly in the locations of inhabitance and the visited places. To avoid these stochastic effects and because of the assumption, the vehicle fleet will be electrified almost completely in 2045, all vehicles were regarded as being electric in a first step. In addition, charging places are aggregated based on the built hierarchical representation of the energy grid (see 2.5).

Fig. 7 shows the distributions of the distances driven during a single trip and over a complete day by private, non-commercial vehicles. Overall, the distances of the trips undertaken by the simulated population using private vehicles as a driver sum up to 18,930 km per day. Assuming an energy consumption of 0.20 kWh/km (approximated via [12]), approx. 3,800 kWh would be needed to recharge the vehicles within the area on a usual working day.

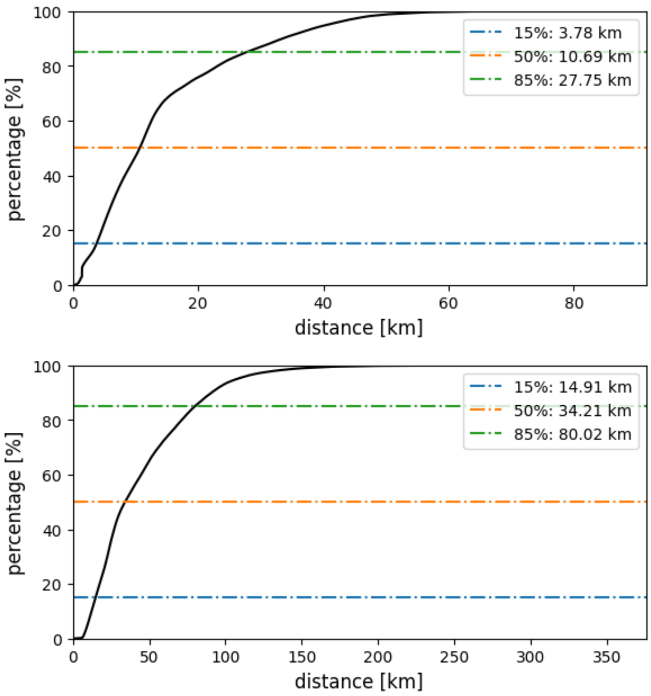

Fig. 7 Cumulative distribution of the distances of single trips (top) and daily driven distances (bottom)

As confirmed by the national mobility survey MiD, vehicles are parking for most of the time. The MiD states that there are never more than 10% of the vehicle fleet in operation at the same time [8]. This is reflected in the distribution of halting durations given in Fig. 8. What is remarkable as well is the high share of 37% of vehicles that are not used during a day at all. Again, this is supported by the MiD, where the number of 40% is given.

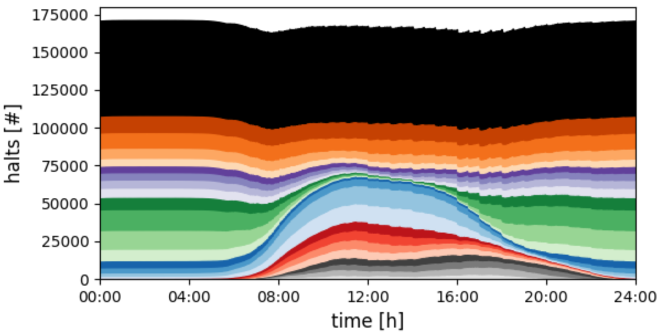

Fig. 8 Number of parking private vehicles assigned to parking duration classes ranging from <1h (bottom) to ≥24 h (top)

The vehicles are then mapped onto the parking infrastructure and the onto the energy grid as described in 2.3 and 2.5, respectively. Fig. 6 show the connection time – sum of the time vehicles are connected to the grid – during a usual day aggregated at the level of transformers. Big parking places can accommodate a large number o vehicles and can as such be used by their operators for facilitating different business models. As such, a distinct evaluation for on-street parking and big parking areas seems to be needed and will be performed in the next project steps.

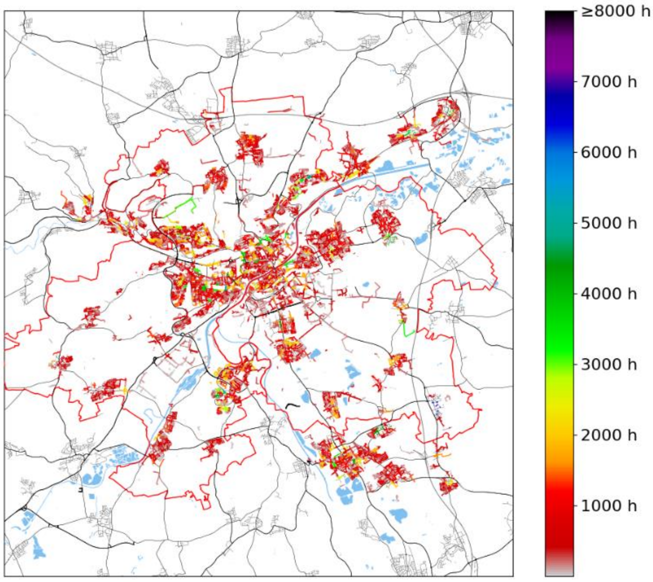

Fig. 6 Connection time aggregated on the level of transformers

4 Conclusion

A system for estimating the additional load on the energy grid generated by a fully electrical vehicle fleet was presented. The system consists of multiple models and data processing steps. It involves a model for computing the travel demand based on per-person individual decisions about the activities performed on a usual day and the respectively chosen modes of transport. The information about trips performed using an own private vehicle computed by this model are passed to a model that resembles charging decisions. Further processing steps map the results to parking positions and then to the energy grid. The system was used to estimate the load on the energy grid within the cities Ulm / Neu-Ulm. A complete electrification was assumed for reducing the effects of stochasticity of the models. In addition, the interactions between single vehicles and the grid were spatially aggregated on the grid levels of switch cells and transformers.

In the next project steps, different scenarios for the development of electrification will be simulated. In addition, scenarios with changes in the infrastructure – such as building a new commercial center that changes mobility patterns –, will be implemented and evaluated for obtaining a more robust prediction.

The presented results show the case of maximum interaction between the grid and the vehicle fleet. In subsequent steps, different business models for bi-directional charging, the performance of charging stations related to the occurrence of fast and over-night charging, and the potential of V2G for increasing the grid's resilience will be addressed. In parallel to extending the evaluation, the tool chain is planned to be extended, mainly by the possibility to simulate different times of the year and the mobility along a week. As well, the distinction between owned and public charging infrastructure should be strengthen within the models as it highly influences charging decisions.

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