Energy Informatics

RESEARCH

Using real mobility patterns to assess the impact of 100% electrified mobility in a German city

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Abstract

Until now, individual motorized mobility has been almost exclusively powered by fossil energy sources. The battle against climate change, however, requires a transformation of the mobility system with the ultimate objective of a full electrification of transport. Ultimately, this will increase considerably the load on the distribution grid both in overall size and through temporarily and locally distributed charging. This paper explores the effects of an assumed full electrification of individual motorized transport on the power grid in a major German city using real traffic data collected from a German traffic panel and employing a microscopic and dynamic travel simulation with the *Simulation of Urban MObility* tool. The main finding of the traffic simulation is that the local and temporary impact on the distribution grid is very sensitive to the distribution of charging stations and their geographical aggregation in transformers. However, behavior change in the form of charging at different points in time and locations or using less power can alleviate local peaks, up to 50% in the simulated scenario. Therefore, this paper addresses the previously uncovered need for a more profound and realistic computation that includes all important aspects of a proper traffic simulation. It further extends the barely covered field of dynamic simulations that operate on real mobility data. With that, limitations arise from the process of transposing driving data into geographical data as it is very sensitive to underlying assumptions. However, we are convinced that the spatialization of charging stations and the randomization of trip assignments represent the most transparent and meaningful way of overcoming these limiting factors.

Keywords: Traffic simulation, Electric mobility, Electricity grid, Charging behaviour, Power profiles

Introduction

What happens if private individual motorized traffic one day is solely based on electric engines? This was the leading question for the presented study. Of course this question has several aspects from local power grid congestion over optimal placement or characteristics of charging stations (CS) to transformer loads and overloads. This paper deals with the latter: Considering real mobility data in one of the big cities in Germany, considering its topology and position of transformers, what would be the additional load on transformers?

Until now, individual motorized mobility has been almost exclusively powered by fossil energy sources and has had a heavy impact not only on CO_2 emissions, thus contributing to climate crisis, but also with regards to NOx and particulate matter among others. Therefore, transport is the main cause of air pollution in cities harming environment and human health (European Parliament 2019). This renders electrification of transport a key technology for developing a sustainable and clean urban mobility in the future.

However, full electrification of transport poses a set of challenges. On the one hand, the additional electricity demand in the future needs to be covered by renewable energy sources. Kühnbach et al. (2020) reckon that 4 million electrical cars will demand around 12 TWh of electricity—compared to the total electricity consumption in Germany of 555 TWh in 2020 (Bundesnetzagentur 2020). According to these figures about 8% of diffusion of electric vehicles (EVs) increases the overall energy consumption by roughly 2%. Obviously, such a linear interpolation does not forecast any future development, as traffic patterns are on the verge of changing due to new ideas of urban life.

A different set of problems, on the other hand, arises from integrating this additional demand into the low voltage power grid, where most of the CS will be positioned. Here, both timing and amplitude of power demand are in the focus. This topic has been dealt with by numerous scientific papers (Eider et al. 2017), however, in most cases simulations were done for artificial environments and/or using artificial data. In Germany, traffic data has been collected regularly based on travel diaries by more than 1500 households with around 3000 people since 1994 (Karsruhe Institute of Technology 2021). In the presented work this data is mapped onto the population of Mannheim, a city in Southern Germany, and a topographic simulation is carried through assuming that all the routes taken by a private car are undertaken using an EV. From this microscopic and dynamic traffic simulation with the *Simulation of Urban MObility* (SUMO) package the power profiles of the necessary CS, which are located at home, work, and in public, are calculated and merged into additional load profiles of transformers. This assumption can serve as an upper benchmark of the impacts of a 100% diffusion of urban EV traffic. The simulation comprises one baseline scenario and three alternative scenarios that are configured with varying charging behavior and initial state of charge (SoC).

The main challenge of the simulation presented in this paper arises from the fact that traffic data consisting of mileage, fuel consumption, and purpose (home, work, public) need to be mapped to the topography of a real city, and CS that currently do not exist have to be positioned so as to satisfy the simulated demand. These "spatialization" tasks make up an important share of this contribution.

The paper is structured accordingly: First, related work is presented, then the methodology explained in "Methodology" section. Section "Data processing" introduces the data, whereas section "Modeling" presents the model and assumptions used to transpose the non-spatial into spatial data. The simulation model is illustrated in section "Simulation", and section "Simulation results and discussion" discusses scenarios and results. The last section, finally, contains a conclusion and an outlook.

Related work

A variety of papers exist that utilize power profiles of CS to assess the additional load on the low and medium voltage grid: Whereas CS today are located by and large in low voltage grids, the impact on the distribution grid is predominantly on the medium voltage grid via an increased transformer load. Most papers, however, are merely based on statistical or deterministic simulation models. The main focus of this paper is the computation of CS power profiles through a dynamic traffic simulation in SUMO (Lopez et al. 2018) based on the representative *German Mobility Panel* (MOP) (Karsruhe Institute of Technology 2021) study. This addresses the previously uncovered need for a more profound and realistic computation that includes all important aspects of a proper traffic simulation. Figure 1 summarizes the analyzed papers and categorizes them based on their simulation approach into papers using a dynamic vs. static simulation method with real vs. synthetic data, and it positions the presented work.

Static simulation and synthetic data

The next set of papers implements a static simulation model in which time is not a factor. The results can be seen as a snapshot of the system run by setting parameters. The first two papers utilize synthetically created data sets. The work by Ucer et al. (2018) examines and evaluates the voltage impact of EV mass penetration on a distribution grid model by using a *Gaussian* distribution to define trip and battery attributes. The second paper by Xiang et al. (2018) develops a new integrated framework for simulating the charging load of EV CS. A model stochastically generates the behavior of EVs and related traffic conditions based on deterministic rule sets and given distribution functions and parameters.

Static simulation and real data

The following papers utilize real data in their static simulation model. The work by Schäuble et al. (2017) synthetically generate multiple consolidated load profiles of EVs based on empirical data of EV mobility studies and varying statistical factors. Erden

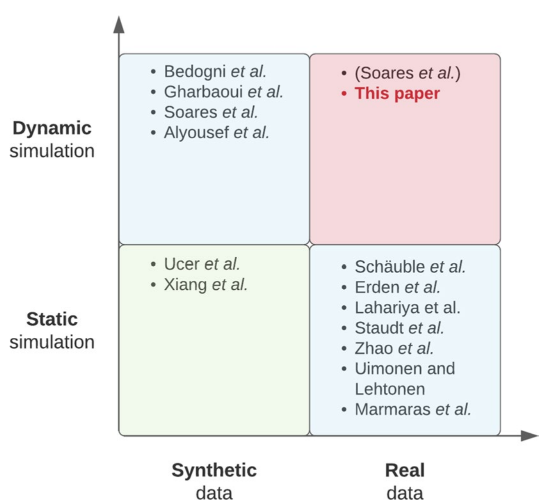

Fig. 1 Classification of related work

et al. (2015) also analyze the constraints on the utility grid by collecting real user driving information, but they generate a statistical model of trips. In Lahariya et al. (2020), Lahariya et al. create a synthetic data generator for EV charging sessions that is based on a real-world data set by implementing various probability distributions. Furthermore, Staudt et al. (2018) propose a decentralized mechanism to include EVs into the congestion management to prevent an overloading of the transmission system with uncoordinated charging. In addition, Zhao et al. (2010) develop a simulation method of large scale integration of EVs in distribution grids to stochastically determine EV charge loads in form of voltage and current congestion. In Uimonen and Lehtonen (2020), Uimonen and Lehtonen simulate load profiles of CS based on charger occupancy data and Marmaras et al. (2017) create an integrated simulation-based approach in which EVs interact with the electric power systems. But all these approaches, albeit using real data, do not explore temporary developments which are key for understanding grid issues.

Dynamic simulation and synthetic data

In contrast to static simulation models, a dynamic model can determine the varying behavior at different times and scenarios. It represents complex traffic environments with unpredictable situations and outcomes. Bedogni et al. (2016) propose a new EV simulation platform to facilitate the deployment of charging networks and services. The co-simulation framework consists of SUMO and *Omnet++* (a network simulator) using artificial data based on state variables. Gharbaoui et al. (2013) implement activity-based EV behavior in SUMO including charging needs and travel demands that are derived from daily activities. Soares et al. (2012) present a simulator for EVs that is used for smart grids and distribution networks while Alyousef et al. (2018) develop a real-time mechanism to enhance the power quality in the energy distribution grid. The main drawback of the cited papers is that they use artificially created data.

Dynamic simulation and real data

Up to this point, synthetic data is used to simulate EVs. In contrast, Soares et al. (2014) present a simulation framework that uses real census and survey data to estimate the activities of households. The setup of the traffic simulation is similar to this paper, but only a small set of electric buses are implemented, and no power profiles are computed directly in the simulation. They rather focus on obtaining vehicle parameters, while the associated power and energy consumption lacks accuracy and reliability.

This paper aims to fill the research gap in this field of dynamic simulations that operate on real data. It utilizes real-world survey data sets from MOP to derive EV models instead of relying on statistical or synthetically created data. Furthermore, power profiles are computed dynamically in SUMO whereas most related papers make use of algorithms and static decision models. This approach overcomes existing limitations of reproducing realistic traffic environments with a comprehensive traffic simulation. With real data and a dynamically computed simulation, current and future conditions can be best depicted. Nonetheless, as stated above potential limitations include the complex conversion of data into dynamic traffic which is addressed and resolved in the next sections.

Methodology

The goal of this traffic simulation is to dynamically compute load profiles of CS in order to assess the additional load on the medium voltage grid via the impact on the transformer load. An EV simulation requires adequate and realistic data models underlying the mobility and charging behavior of the vehicles. However, the very rare data sets on EV behavior are mostly characterized by innovators' behavior, not representing the mobility needs and habits of the general population. In order to mitigate this issue, data from the so-called "MOP" survey of 2018/2019 is used. This data set is provided by the *Karlsruhe Institute of Technology* and is a longitudinal survey that yearly collects data about the travel behavior of the German population. It studies people's everyday mobility as well as mileage and fuel consumption of internal combustion engine (ICE) vehicles in private households (Karsruhe Institute of Technology 2021).

Assuming that travel demand of ICE vehicle drivers (which make up almost all of the panel participants) will remain the same independently of the engine technology employed, this data set is used to simulate the power and energy demand of an electric-only mobility. Figure 2 depicts the general approach to this endeavor. As urban mobility patterns are currently changing, it will provide an upper limit of the electricity demand from individual mobility.

One of the biggest challenges is to map the data from the MOP study onto topographical data, here represented by the road network of the German city of Mannheim. The MOP data set consists of travel diaries from participants that include features such as date or distance driven. Due to privacy issues, no specific geographical information on direction or routes are available. Therefore, assumptions have to be made to optimally transpose these non-topographical patterns into topographical data for the dynamic and microscopic traffic simulation in SUMO. An EV behavioral model is derived that translates the trip diary into actual mobility and charging patterns that can be implemented in the simulation. For this process, households are aggregated into clusters where they are averaged with regards to attributes, such as time and distance. This model, therefore, describes where, when, and how often a typical cluster household drives during the regarded time span. The EV behavioral model is used to derive scalable and realistic EV mobility patterns that are based on non-topographical patterns. Otherwise, the translation of single ICE vehicle routes into EV patterns would be inefficient, not scalable, and difficult to configure. Also, households are categorized in clusters to enable easily

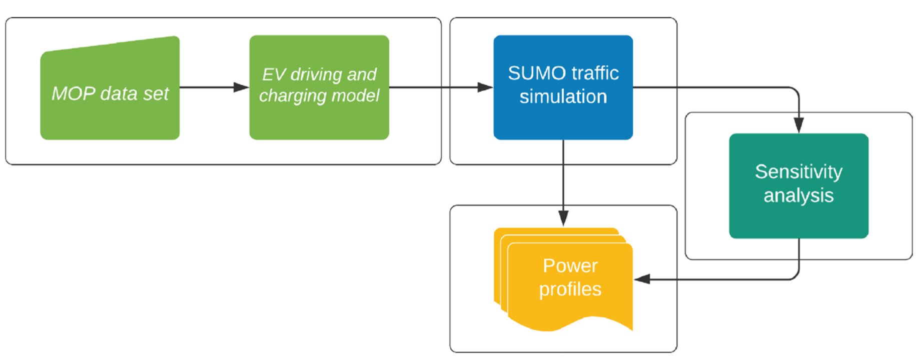

Fig. 2 Methodology of this work

extensible and transparent travel patterns that represent realistic and aggregated EV behavior instead of looking at single and nonuniform households. As there is no information on the exact location of their destinations, but only on the purpose of the trips, random routes are created that are distributed across the city. These routes incorporate the correct distance for each household and are assigned to the households to match the driving behavior with the data from their diaries, thus adding EVs and CS to the road network. Following this underlying data model, the EVs drive and charge in the simulation that represents the topographical counterpart of the non-topographical MOP data set. As a result, static and anonymous travel data is translated into actual travel patterns in the map of Mannheim.

In total, one baseline and three alternative scenarios, all with 100% EV diffusion, are deployed. For these scenarios, the frequency of charging and the initial SoC are configured to explore the impact on the grid under various conditions. The baseline scenario implements EVs with a randomized SoC and a maximum charging strategy to make EVs charge whenever possible. The other three scenarios are executed with different parameters, such as 20% SoC or adjusted home charging. The outcome of these scenarios are the power profiles of the CS.

To assess the impact from charging on the low voltage grid, several CS are spatially aggregated into transformers in Mannheim. Two are presented in this work, located in environments with different characteristics and covering different numbers and types of CS. These transformer power profiles represent the additional charging load on the grid for the baseline and alternative scenarios.

Data processing

The most relevant files from the MOP study for the simulation contain information about households, vehicles, and trips. They are preprocessed to filter out missing, erroneous, and unwanted values. This includes operations such as cleaning, normalizing, transforming, extracting, and selecting relevant data values. After this step, 1495 participating households and their 33,318 trips by car are used for further processing. ICE vehicles are substituted by respective EV car segments, such that EV specifications can be added to the cars as additional attributes. This enables the transition from ICE cars to EVs, and the routes can be translated into EV routes by later incorporating charging operations. The EVs are categorized into small, medium, and large segments that are represented by the most popular vehicle for each segment based on the number of new registrations in Germany in 2021 (Kraftfahrt-Bundesamt 2021). These EVs are equipped with a 41 kW, 50 kW, and 64 kW battery respectively.

A big advantage of the MOP study is the trip diary of car owners that also includes the purpose of the trips. Based on this, the location of the car can be derived, which makes it possible to simulate charging behavior. Trips can be assigned to twelve categories which for reasons of simplicity are condensed into the three categories: "home", "work", and "public", removing another 3138 untypical trips such as "trips to hotel". This results in 30,180 trips with destinations also representing the location of the respective CS.

Figure 3 shows the relative distribution of *arrival times* at home, work, or public destinations. For each hour of the day, the graph displays the share of *moving vehicles* that arrive at the respective location. This roughly reveals when and where the vehicles are

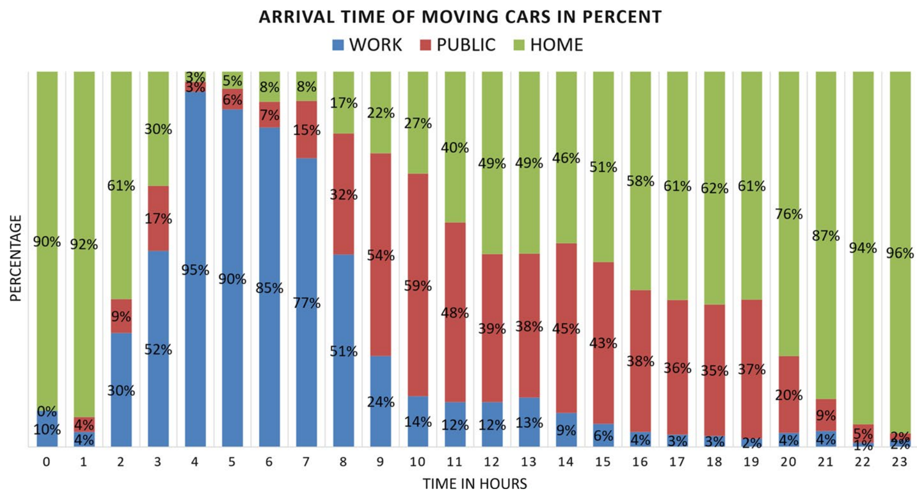

Fig. 3 Arrival time of moving cars in percent

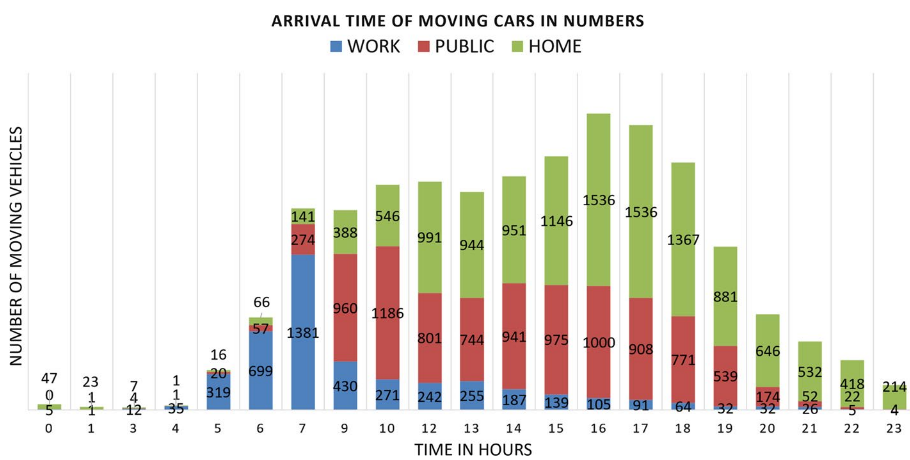

Fig. 4 Arrival time of moving cars in numbers

traveling to get a first understanding of possible charging opportunities. However, it does not incorporate the duration of the stay or vehicles that are not moving, so that the actual number of all vehicles at a specific time varies. Nonetheless, it clearly shows that a majority of the moving cars, e.g., 77% at 7 a.m., go to work in the morning while most of the moving cars go home in the afternoon and evening. Public places are visited throughout the day. This leads to the observation that charging load at work is the highest in the morning and decreases as cars get fully charged. CS at public locations might see peaks in the morning and in the afternoon. The charging profile at home probably increases in the late afternoon as households arrive home from work and charge their EV overnight.

Figure 4 shows the same distribution of *arrival times* of *moving vehicles* but in absolute numbers. It presents the number of trips that end at home, work, or in public at any hour of the day and indicates how the 30,180 routes are distributed in terms of time and location. The busiest hour for work is at 7 a.m. with 1381 moving cars and the peak for home lies between 4 p.m and 5 p.m. with 1536 traveling cars. The peak for public locations consists of 1186 cars at 10 a.m, and the arrival rate is relatively stable until 5 p.m. Very few vehicles are moving in the time after 9 p.m until 5 a.m, and they mostly go to their homes.

Modeling

Assumptions

Closely connected with the filtering of data, two additional assumptions relating to trip distance and household types are made.

- **Assumption 1**: *Limit trip distance to 50 km*

  The distance of the 30,180 available trips ranges from 0.1 km up to 780 km. The MOP data merely differentiate between urban area data and rural area data thus not supporting the decision between "inside" or "outside" city borders. Due to the geographical extension of the city of Mannheim, we assume that single trips above 50 km exceed the city boundaries; on the other hand would we assume these long trips beyond 50 km were limited to the city region this would enforce high charging activity, distorting the impact on transformers. Therefore, routes beyond 50 km are dismissed. As a result, five of 1495 participating households and 1598 routes are deleted that represent a share of 5.3%. The remaining 94.7% of the original data set, i.e., 1490 households and 28,582 trips, is further used. The trips now have a mean distance of 10.11 km. When this value is multiplied with the average number of trips per day from the data set, i.e., 2.7, the result is 27.3 km per day. This matches well with the daily driven distance of a person calculated by the MOP study, which is 28 km per day and car (Ecke et al. 2020). Figure 5 shows how the total set of routes (including the ones surpassing 50 km) are distributed according to distance. It clearly shows that the majority of trips are under 50 km, with the peak being around 3 km.
- **Assumption 2**: *Only households from urban areas*
  The location chosen for the simulation is the German city of Mannheim. In order to align the characteristics of the households with the urban situation, households that

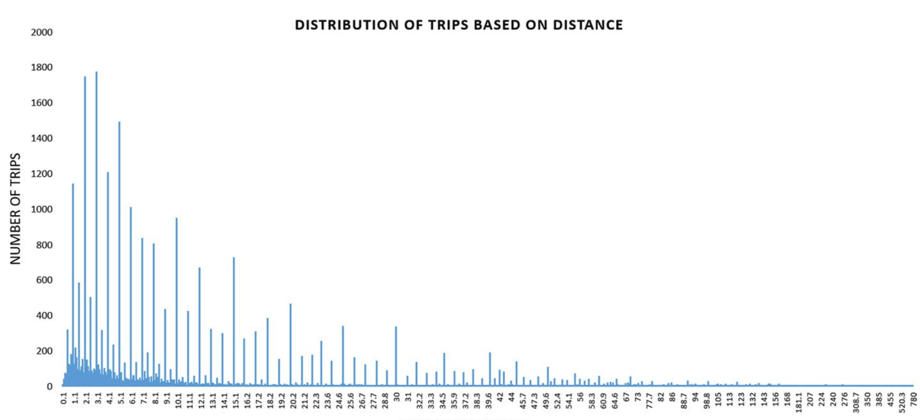

Fig. 5 Distribution of trips based on distance

live in rural areas are dismissed. This reduces the number of simulated households by 45.8% from 1490 to 808. This is the final number that only includes households that have a trip diary, drive routes to home, work, or public with trips under 50 km, and live in an urban area. The final number of trips thus includes only trips from **808 urban households**. All together these are **13,872 trips** as summarized in table 1.

Representative households

The next step is to derive an EV behavior model for these households that can be implemented in the traffic simulation. Instead of computing traveling and charging patterns for each single household, they are clustered into a number of representative households that combine characteristics and properties. This makes it easy to scale the number of simulated households to higher levels. New representative households can be added by just increasing the size of the cluster, i.e., the number of typical households in the cluster. This measure also greatly improves compatibility with the simulation and facilitates the setup process. Changes can be efficiently applied to all concerning households, and behavioral patterns can be controlled and configured in an uncomplicated manner. For example, the number of simulated cars can be scaled up to the actual number of cars in Mannheim to project the real population of the city, just by increasing the size of the cluster.

The criteria used for creating suitable clusters of representative households are the distance driven, number of trips, size of households, and the trip to work.

As a result, 16 clusters are created that comprise varying numbers of matching households. The households inside one cluster are averaged with regards to the clustering features, so that in the end a cluster consists of a number of identical households typical for that cluster. Each cluster contains the following features.

- **General features**: cluster ID, number of households, share of cluster in percent, car segment, number of trips, and distance in km
- **Trip features**: departure time, start location, distance in km, and final location of every trip

These features are either readily available or directly derived from the data, e.g., the average trip distance of a cluster household which is computed from the total distance in km of all cluster households and the total number of their trips. In order to determine the behavioral patterns, all trips with the corresponding trip purpose are extracted and

Table 1 Operations on the number of trips—correct template

Operation	Number of trips
Original	71,189
Of these: Trips by car	33,318
After deleting rare trip purposes	30,180
After deleting trips beyond 50 km	28,582
After deleting rural households	13,872
Result: 808 urban households	13,872

analyzed for each household. For example, cluster number one has 75 households and a total of 291 home trips and 350 public trips. If the number of visited locations matches the number of total trips, the departure time for each purpose is calculated with the median value. If the household visits more than two places, i.e., has more than two trips, then the order and quantity of the trips have to be assessed, e.g., whether the car goes to work or to public first or whether it goes to public or work twice. The trips in between the start and end at home need to be assigned accordingly.

The following section explains the assignment of trips in a cluster using the original data of the total number of trips of the original cluster households. The departure times of the trips indicate how these are distributed throughout the day. To calculate the starting time of single trips to a certain purpose location in the regarded time span, the median of the corresponding trip departure times of the cluster is used. In the case of two trips to a certain location, the two tertile values can be utilized and for three trips, the first, second, and third quartile values of departure times of the cluster are assigned. Trips to work mostly start in the morning, trips to public are usually in the afternoon, and return trips to home are in the late afternoon. This makes it easier to assign the order of the specific trips. The values are retrieved based on the same method to ensure consistency. Additionally, the validity of the trips is checked with a histogram that visualizes how trips to a specific location are distributed. Two histograms of cluster 6 for the trips to work and trips to home are shown in Fig. 6. They depict the distribution of trip departure times, and they are used to verify the assignment of trips that uses median values. The time is rounded in ten-minute steps for a simplified and comprehensive implementation.

After this has been done for all 16 clusters, each representative cluster has a behavioral pattern that is based on the data of the MOP study. This behavior model defines how much, how often, when, and where the EVs drive and assumes possible charging opportunities during the stay at a location. It is used as the data basis for the implementation in SUMO. Figure 7 shows the first eight clusters of the behavior model. *ST*, *SL*, and *FL* stand for starting time, starting location, and final location respectively, whereas *H*, *W*, and *P* mean home, work, and public. For each cluster, the attributes and trip characteristics are listed that have been explained in this section. For example, cluster number 3 includes 136 households that equals a share of 18.07% of all 808 households. They take two trips with a total distance of 9 km and possess an EV from segment 4, representing a small EV that is equipped with a 41 kW battery and that has an energy consumption of

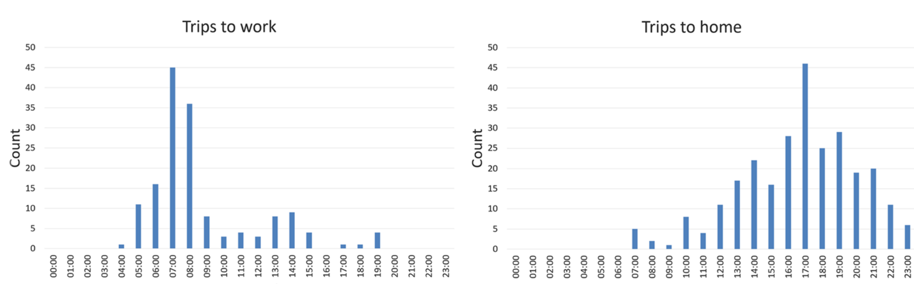

Fig. 6 Histogram of trips to work (left) and trips to home (right) of cluster 6

Cluster	#	Ratio	Car	# Trips	# KM	#1 ST	#1 SL	#1 KM	#1 FL	#2 ST	#2 KM	#2 FL	#3 ST	#3 KM	#3 FL	#4 ST	#4 KM	#4 FL	#5 ST	#5 KM	#5 FL
1	75	9.28%	3	2	13	12:40	H	6.5	P	15:00	6.5	H									
2	69	8.54%	3	2	18	08:00	H	9	W	16:20	9	H									
3	146	18.07%	4	2	9	12:20	H	4.5	P	14:50	4.5	H									
4	71	8.79%	3	2	16	8:10	H	8	W	16:00	8	H									
5	11	1.36%	2	4	19	10:40	H	4.75	P	12:20	4.75	H	12:50	4.75	P	15:40	4.75	H			
6	30	3.71%	3	4	24	7:00	H	6	W	13:10	6	P	16:30	6	P	17:50	6	H			
7	42	5.20%	6	4	25	10:50	H	6.25	P	12:10	6.25	H	14:20	6.25	P	16:20	6.25	H			
8	73	9.03%	4	5	33	9:00	H	6.6	W	11:30	6.6	P	13:50	6.6	H	15:30	6.6	P	17:30	6.6	H

Fig. 7 First eight clusters of the EV behavior model

17.2 kWh/100 km. The first trip starts at home at 12:20 p.m. and ends at a public location. The return trip to home is at 2:50 p.m. with a distance of 4.5 km. The car can charge at the public location and after arriving at home.

Charging behavior

Charging behavior modeling is made up of two components: frequency of charging and charging mode.

Frequency of charging in the baseline simulation is modeled as a "maximum charging strategy" that makes them charge whenever and wherever possible as long as this conforms to the time schedule. Vehicles always and only leave the CS if it is time to resume their trip to the next destination. For a basic approach, EVs use all CS on their routes if the SoC is smaller than their maximum battery capacity. It is important to note that EVs only stick to their predefined routes. They do not autonomously deviate from their trip or time schedule to visit other charging stops, e.g., based on their SoC. This preserves the underlying behavior model that is derived from the MOP data but at the same time slightly adjusts behaviour accommodating charging necessities.

The charging mode refers to the desired SoC after the charging process is completed as well as to the CS power which is given by its location. In the simulation, the batteries are charged to the full capacity of 100%. This has been implemented to assess the full impact on the charging network.

Simulation

Simulation software enables complex simulations of road conditions, road transportation networks, and heterogeneous traffic (Pell et al. 2017). This work computes charging profiles by implementing a dynamic traffic simulation with the microscopic and continuous simulation package SUMO instead of relying on static algorithms and decision models. It incorporates varying and complex traffic environments and operates on realistic data from the MOP study to fill the research gap for dynamic simulations based on real data. SUMO is freely available and was mainly developed by the Institute of Transportation Systems at the German Aerospace Center. The multi-modal simulation comes with a large set of model extensions, creation tools, and up-to-date enhancements. SUMO can also handle large networks and offers an extensive graphical user interface that visualizes all objects and steps of the simulation.

Figure 9 presents the architecture of the implementation. The process starts in the bottom right corner with importing the map of Mannheim from *OpenStreetMap* (OSM)

Fig. 8 The road network in SUMO (OpenStreetMap 2021)

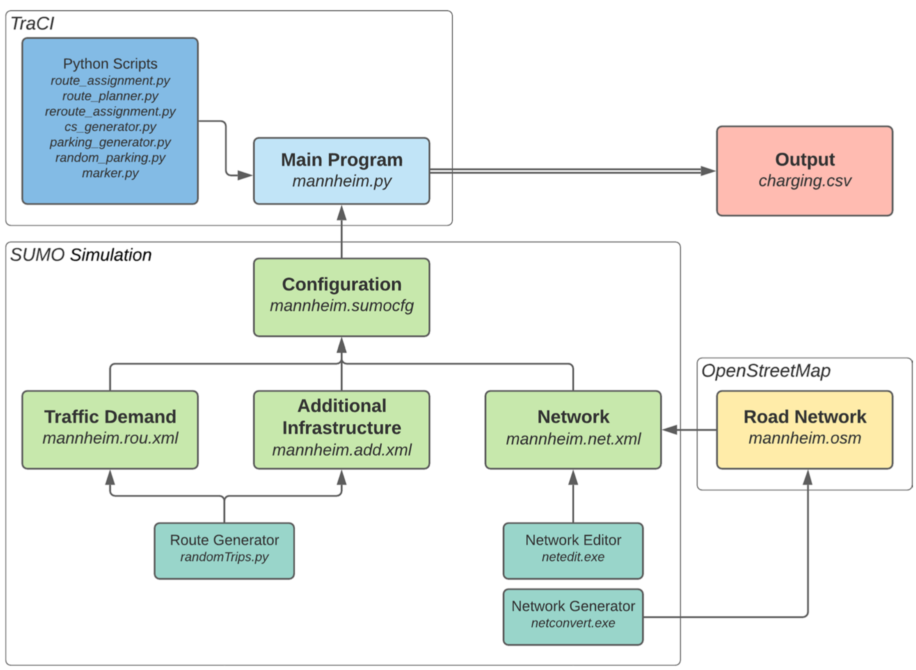

Fig. 9 Architecture of the SUMO simulation

(OpenStreetMap 2021) that is converted into a XML-file and read by SUMO. The road network of the simulation is depicted in Fig. 8 and shows an excerpt of the imported map of Mannheim. The main input files are needed in the configuration to run the simulation. Then, the main python program starts and controls the whole simulation. Smaller python scripts facilitate the setup in the *Traffic Control Interface* (TraCI).

As mentioned, the MOP data set does not provide any information about the geographical location of home, work, or public places. It only indicates the distance and time of the trip. Therefore, the derived EV behavior model also consists of just the distance, time, and the type of location, i.e., home, work, or public. In order to project the data into the city of Mannheim, the tool *randomTrips* is used to generate randomly distributed routes across the city for all 808 households while households within a cluster are assigned the same distance. This creates a set of trips with a random source and destination edge inside the road network based on given parameters such as the distance defined by the cluster. This means that the routes are random in terms of directions, but still retain the exact distance from the MOP data. The source later represents the home location whereas the end of the trip refers to the location of the next destination (home, work, or public) where in specific cases (see section) a CS is placed creating a charging opportunity. Intermediate stops are also modeled according to the behavioral model shown in Fig. 7.

This whole process translates the time and distance data into actual mobility and charging patterns of clusters to dynamically create charging profiles at CS. Based on the start, intermediate, and destination edges of these routes, the home, work, and public locations can be assigned to the households and their CS can be added to the network.

After the simulation finishes, the program stores all charging events of every CS in an output file. This output file is further processed in *Jupyter Notebook* to create charging profiles that visualize the additional load of selected CS on regional transformers during the time span of this simulation.

Configuration of SUMO

Time in SUMO

SUMO uses a time step of 1 s per default. Therefore, 86,400 s are needed to simulate a full 24-h day from 12 a.m. to 12 a.m. of the next day. The first vehicles leave their home at 6:50 a.m. while no information for the period before the first trip is available. The last charging event of the day ends at 10 p.m.

EV initial SoC

The initial SoC of EVs is a crucial factor that significantly affects the simulation as it determines the necessity to charge. It is generally recommended operating the battery between 20% and 80% or 90% (Kostopoulos et al. 2020). Continuously operating the EV below 20% and beyond 90% harms the battery and can lead to capacity degradation. Nonetheless, charging beyond the upper limit is not as harmful as operating below 20% SoC and might be even necessary at times, e.g., for longer trips (Kostopoulos et al. 2020). Therefore, in the baseline scenario, all cars are initially equipped with a randomized SoC between 20% and 80% to incorporate realistic battery values. Alternatively, a static low initial SoC of 20% is implemented to look into more extreme cases and experience a bigger impact on the grid. This case is supported by the outlook on future charging infrastructure (BMVI 2020) that also suggests 20% as the initial SoC for their EV study.

These values are used to initialize the battery since no information from the past day is available. The following day (if simulated) would not start with the generated value, but with the SoC from the night before.

One EV per household

Although households can have multiple cars, only one car per household is implemented in the simulation. This simplifies the implementation and control of the EV behavior model. This means that for 808 households, 808 EVs are computed, which is equivalent to the EV diffusion level of 100%. They combine the characteristics of all cars within the household. More cars in a household would not make a big difference, as the associated trips would just be distributed among the available cars without changing the total energy demand and thus the grid load. Households can be easily scaled up after the simulation by extrapolating the corresponding power profiles.

Assignment of charging stations

The German Federal Ministry of Transport has published an outlook on the charging infrastructure for the year 2025 and 2030 (BMVI 2020). This forecast identifies the needed infrastructure of public and private CS as they are crucial to the successful transition to electric mobility. This outlook is essential to correctly model the future charging infrastructure and to assess the corresponding and potential power load on such. According to this report, 42% of households will have access to a private CS at their residence. Additionally, it is calculated that 75% of households will have the ability to charge their EV at their work place (BMVI 2020). Regarding publicly available charging possibilities, the European Commission recommends having at least one charging point for every ten EVs (European Commission 2014). In the study on the potential charging infrastructure by the the German Energy Agency, this 10:1 ratio is also identified. Especially in urban areas, one charging point should supply ten EVs with sufficient energy for recharging (Dena 2020).

These projections and requirements are adopted for this traffic simulation and are used as a suitable input to look into the impact of a full electrification of individual motorized traffic, i.e., an EV diffusion rate of 100%. In the case of 808 households, this means that 340 home, 81 public, and 350 work (out of 466 available work locations) CS are implemented. In the simulation, 340 randomly selected households are able to charge at home. The remaining 468 households are assumed to have a parking spot at home where the EVs can park after arrival. Also, every household is initially assigned a charging point at work (if it goes to work), at public (if it goes to public), or at both locations (if it goes to both). They are able to charge at these work and public locations to capture the full impact on the grid and to compute charging profiles under maximum utilization. Additionally, this ensures that every household is able to charge during the day even if they cannot charge at home. The remaining households that do not drive to work also represent those that do not have a CS at work to match the forecast of BMVI (2020).

After placing these "single" charging points, work and public CS are virtually aggregated into CS consisting of various charging points in order to match the actual number of CS. These charging points within a specific radius are "virtually" clustered into bigger CS by applying the *k-means clustering* method based on geographical distance. Therefore, one charging point can be seen as a part of a bigger CS that includes multiple distributed charging points and that combines their charging profiles.

In the simulation, they cannot be "physically" combined into one CS to maintain the actual distance of each car to their own destination. Otherwise, this would alter the distance of the trips to a "physically" combined location for every visiting car, such that it would deviate from the underlying data of the MOP study. This ensures that the real mobility patterns are correctly implemented in the simulation, resulting in realistic charging profiles. However, no constraints are incorporated for these combined stations. It is assumed that they have unlimited capacity and can charge every EV that arrives at the station. This has the advantage that the impact of 100% electrification on the grid can be assessed, unrestrained congested EVs, which is a precondition for a well functioning electric mobility system. As an additional advantage, this is in line with the used EV model of SUMO that does not allow for changing the configuration or occupation of CS during run time.

Charging power of charging stations

All CS have only one charging point as explained above and charge with either 7 kW at home or work, or with 22 kW in public. This represents typical power rates in Germany in 2020 (Bundesnetzagentur 2021). It is assumed that these power rates can always be achieved. Realistically, many factors can reduce the charging power. The power rate usually decreases as the battery gets charged and has a significant drop in power when the battery reaches 80% SoC (Kostopoulos et al. 2020). Also, the power rate might not output the maximum power when multiple cars are sharing a CS. These configuration settings could be easily changed, as they are representing current conditions, whereas both efficiency and power draw of EVs will change considerably in the future.

Road network and routes

OSM is a collaborative open-data project that creates free and editable geographic maps (OpenStreetMap 2021). It provides the option to export a selected part of the map as an OSM-file that creates a digital one-to-one illustration of the real world. For the simulation, the city of Mannheim is exported, and the resulting computed network file defines every part of the network with its attributes including all streets and highways in the form of edges that are connected by junctions and traffic lights.

The next important component of the simulation is the route file. In the first part of the file, the three EV segments small, medium, and large are created and assigned to the households. The second part includes the time schedule and routes of all simulated cars that are ordered in chronological order based on their departure time. The routes for each car are randomly assigned by generating a set of random trips for the network by choosing a source and destination edge at random and creating the routes along the real road network. The source later represents the home CS or parking area whereas the end of the trip refers to the location of the next destination (either work or public). Therefore, the start, intermediate, and destination edge from the route file represent randomly distributed home, public, or work locations in the city where a CS or parking area needs to be placed. 466 work and 593 public CS within a specific radius are internally clustered into bigger CS. Through the clustering process, the number of CS recommended by the e-mobility forecasting studies (BMVI 2020; European Commission 2014), i.e., 81 for public and 350 for work, can be achieved.

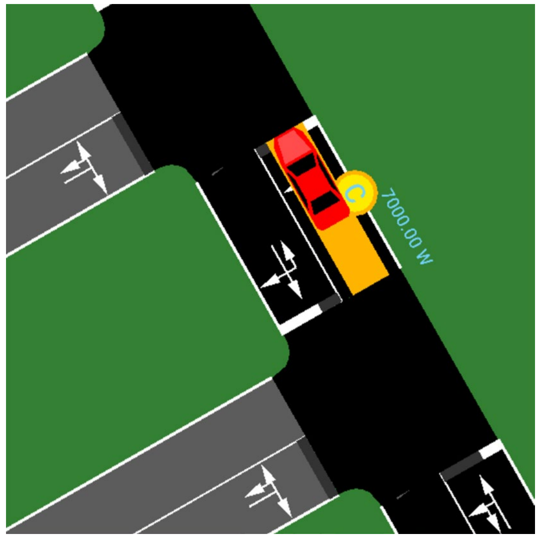

Fig. 10 Charging process in SUMO

Figure 10 displays the visualization of the simulation in SUMO: An EV is charging at its respective CS during its route.

Simulation results and discussion

The power profiles of CSs are computed based on the output of the simulation and the clustering process. The simulation is set to simulate a full 24-h day with a time step of 1 s, thus representing 86,400 s. Due to the big network and the high number of vehicles, the simulation usually takes 2:05 h to finish as it runs on a single core and there is no support for multi-node parallelization yet. Also, standing cars slow down the computation significantly, which is inevitable for the use case of this paper (Simulation of Urban MObility 2021). The simulation is executed on local and remote computing servers.

In most cases, CS are connected to the low voltage grid where the additional electricity load caused by EV charging can be measured. Therefore, transformers in the low voltage grid can be used to analyze the overall impact of a predefined geographical area since they include all nearby CS of all types. Therefore, load profiles of CS are geographically merged on real transformer substations to assess the additional power load on the local electricity grid. This is applied under the assumption that energy demand of 100% EV penetration can be fully met to capture the whole impact.

As there are no publicly available load profiles of transformers to assess the impact of EV charging on the distribution grid, the location of transformers are used to look into the additional energy load on a specific region. The locations of the transformers in Mannheim are provided by a customized map based on OSM (123map 2021). Two exemplary transformer stations from the map are selected to assess the additional load in these two areas. These transformers represent different local contexts and they contain different numbers and types of CS. The first transformer includes six CS in a residential area of which the majority are private CS at home. In contrast, the

Table 2 Overview of the scenarios—correct template

	Starting SoC	
Charging behaviour	**RandomSoC**	**SoC-20%**
MaxCharge	BL: Random & Max	20% & Max
Charge@Home	Random & @Home	20% & @Home

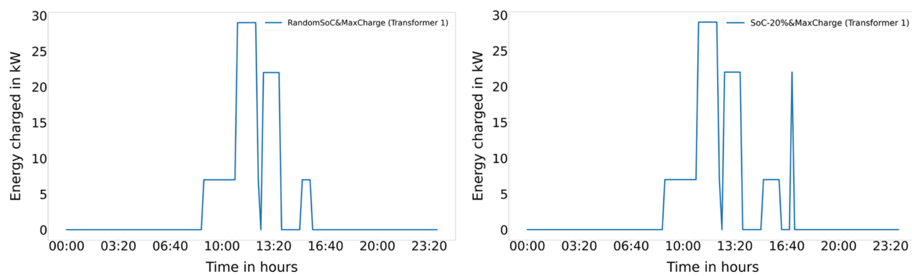

Fig. 11 Power profiles of transformer 1 for the baseline scenario with randomized (left) and 20% (right) SoC under the MaxCharge strategy

second transformer covers 13 CS in a central area with only two home chargers and eight public CS with 22 kW. These different characteristics enable a diversified output in the simulated scenarios and are used to represent common transformers in cities.

The size of the area that a transformer covers varies greatly and depends on a variety of factors. For the purpose of this work, a standard radius of 350 m and a coverage area of 0.4 km^2 for urban areas is chosen (Engmann 1959). This assumption can also be observed in the customized OSM map (123map 2021), where most transformers have a radius between 200 and 400 m.

Scenarios

Four scenarios are configured and implemented in the simulation which differ according to the charging behavior and the SoC at the starting time of the simulation. On the one hand, charging behavior is modeled as either taking any opportunity to charge or to only charge at home. The initial SoC, on the other hand, is either randomized or, in order to explore an extreme situation, fixed at a static SoC of 20%. This leads to the four scenarios in Table 2. The baseline scenario is configured with a randomized beginning SoC between 20% and 80% and the maximum charging strategy.

Results

Baseline scenario: RandomSoC & MaxCharge

The baseline scenario looks into the situation of randomized SoC values ranging between 20% and 80%, assuming that, as explained above, to save battery life-time people charge within this range and have some left-over battery SoC from the day before.

Due to the MaxCharge strategy, people charge their cars as soon as there is an opportunity to do so and up to capacity. For both transformers this results in a slightly skewed distribution of aggregated charging processes to the late morning and early afternoon with a dip at noon (see Figs. 11 and 12). Transformer 1 (left side in Fig. 11), which

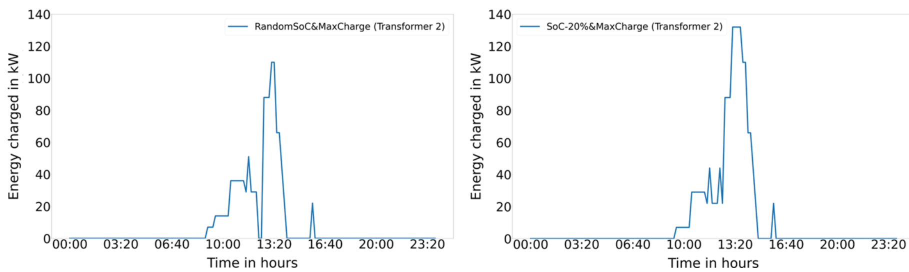

Fig. 12 Power profiles of transformer 2 for the baseline scenario with randomized (left) and 20% (right) SoC under the MaxCharge strategy

aggregates only six CS (three home, two public, one work) therefore experiences a relatively small extra peak load of 29 kW between 11 and 12 a.m. and an even smaller peak in the early afternoon at around 1 p.m. This is also due to two home CS that do not charge at all as its vehicles return fully charged.

The second transformer station includes 13 CS within its 350 m radius and covers two CS at home, three at work, and eight in public. In this geographical area, seven distinct household clusters receive their energy from the same distribution grid. Since more stations are combined into one overall energy profile, just due to the geographical distribution of the necessary CS, the variation in power demand from the additional EV load is much higher and a much greater peak load of 110 kW is observed (see Fig. 12). Whereas for transformer 1 the maximum of the load was created in the very late morning resulting in a peak around noon, here the load is concentrated during a few hours in the early afternoon, around 1.5 h later. Also, the peak load is more than four times higher than in transformer 1. This can be explained by the high number of 22 kW public charging stations in the area as opposed to the majority of very slowly CS in households (7 kW).

For both transformers, the power demand in the afternoon is reduced due to freshly filled batteries, so that the overall pattern and peak times remain roughly the same. However, the differences in sizing may result in a very different impact on the low voltage grid, depending on the original power profile and utilization rate of the transformer without EVs.

Scenario 2: SoC-20% and MaxCharge

Whereas the first scenario was based on the assumption of a randomized SoC, the second scenario tries to asses the extreme impact of a situation where private EV users (a) all start with the same SoC and (b) all charge their batteries to full capacity at every opportunity they get. For transformer 1, at first glance, the result does not change considerably, however looking more closely, it gets obvious that depending on the times when people come back and the distances driven, they create a second peak in the afternoon which is almost as high as the one around noon. The impact of this extreme SoC assumption is much higher at transformer 2 where the number of CS is higher and more 22 kW-CS are involved. Here, the load becomes more concentrated in a shorter time-interval resulting in an extra peak of 132 kW, which is almost 20% higher than for the case of distributed SoC. This shows how little deviations in assumptions can have a high impact of the projected grid pressure from EVs—and this stresses the importance of

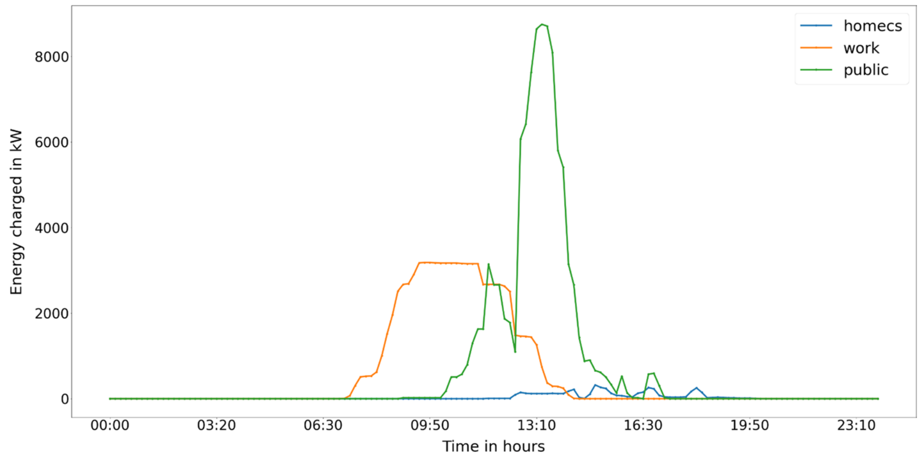

Fig. 13 Aggregated home, work, and public power profiles, here scenario 2

influencing the charging behavior of EV drivers which will be touched upon in the next two scenarios.

In Fig. 13 the individual power profiles of aggregated home, work, and public CS are shown. It presents the different pattern and distribution of energy demand for each type of CS in this scenario. Work CS have their highest peak in the morning whereas public chargers reach their much higher peak in the afternoon. Due to the implemented MaxCharge strategy, the home power profile in the evening is significantly lower compared to the other types of CS.

Scenario 3: RandomSoC and Charge@Home

In the next two scenarios, the charging behavior of households that own a CS at home is adjusted. It is assumed that they no longer charge at work or in public, but exclusively charge at home. This might be a realistic assumption for households owning solar panels (Jabeen et al. 2013), which will be enforced for new buildings in Germany before long, or for the case of people returning in the evening and plugging their EV at their private CS.

340 households own a CS, and their vehicles now are modeled to only charge at home which greatly increases the number of charging processes at home. This is because in the MaxCharge scenario, only a minority of charging processes are implemented at home even for the people with private CS because the EVs arrive at home with an already fully charged battery as they always charge at work or public throughout the day. The EVs without a home CS follow the same behavior as previously defined, that is they charge their EV up the full capacity of their battery whenever they get the opportunity to do so.

For the first case, the randomized SoC ("RandomSoC"), the energy consumption at home increases massively, while the energy demand at work and in public is noticeably decreased as expected. While the peak load for home increases, the demand during busy hours in public and at work is almost nonexistent. These results indicate that an increasing share of vehicles that charge only at home significantly shifts the energy demand away from work and public. Aggregated into transformer 1 (see Fig. 14), which is dominated by home CS, this results into a power profile almost non-overlapping with the power profile of the max charging behavior. The difference

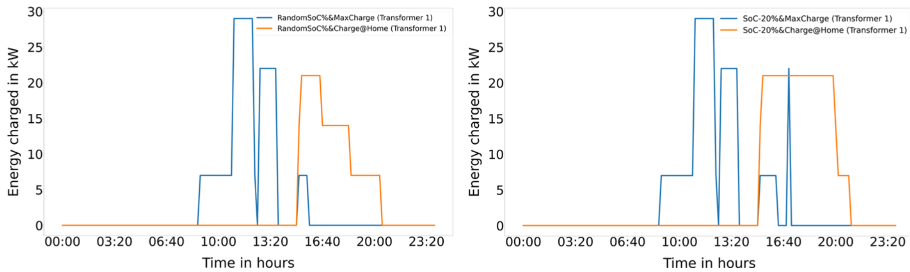

Fig. 14 Power profiles of transformer 1 for the scenario with randomized (left) and 20% (right) SoC, comparing the Charge@Home assumption with the MaxCharge strategy

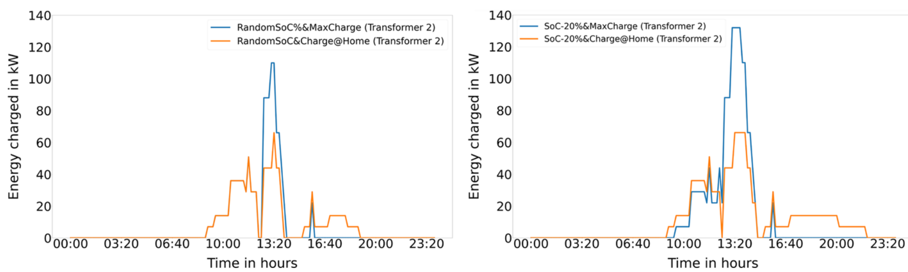

Fig. 15 Power profiles of transformer 2 for the scenario with randomized (left) and 20% (right) SoC, comparing the Charge@Home assumption with the MaxCharge strategy

between the maximum and home charging strategy also has an effect on the energy consumption of the transformer. In the case of randomized SoC, the energy consumption in this scenario is nearly 20% lower than in the baseline scenario (RandomSoC & MaxCharge). EVs charge 92 kWh less at CS of transformer 1 when their behavior is adjusted to home charging, reducing the additional energy load from 512 kWh to 420 kWh during the day because they charge elsewhere in Mannheim. At the same time, as the charging is done upon returning home and differences in the number and distances of trips build up during the day, the power profile is considerably flattened compared to the original charging behavior.

This observation is reinforced for the case of transformer 2 in Fig. 15, which, as should be remembered here, in contrast to transformer 1 aggregates a higher number of CS that are dominated by public and work CS. Therefore, the peak load is not only drastically reduced but also the energy consumption drawn from this transformer decreases. For this scenario with randomized SoC, the home charging strategy reduces the energy consumption by 10% compared to the maximum charging strategy. The total additional energy load of transformer 2 goes down from 1192 kWh to 1065 kWh for the regarded time span of 24 h.

Contrary to transformer 1, here charging process are distributed more evenly during the day and partially shifted towards the evening (originating from the home CS), but the time-shift is not as conspicuous. This alternative charging behavior avoids high peak loads in public during the day but might put additional pressure on the grid in the evening and night.

Scenario 4: SoC-20% and Charge@Home

This scenario brings about the most radical changes assumed, as the bulk charging needs with a high spike around noon caused by a static starting SoC are more dispersed during the day.

For transformer 1, charging process are mostly delayed and spread out during the later afternoon and evening, comparably to scenario 3, i.e., RandomSoC & Charge@Home. In the case of transformer 2, with a much higher share of work and public CS, the original peak at around 1:20 p.m. is less than 50%. The charging energy is not only reduced by nearly 5%, but again shifted towards the evening, lingering much longer than even for scenario 3.

Discussion

The results of the simulation show that each type of CS, i.e., home, work, and public, has a distinctive pattern of energy demand with regard to the amplitude and temporal distribution, i.e., a very typical power profile. Also, the characteristics of the peak load, which is a relevant factor for load assessment, vary greatly between those types. The pressure that driving needs from real data puts onto a real low voltage grid, however, depends on a variety of factors that relate to the geographical distribution of CS and type of CS (due to different power draws), to car features as the initial SoC that impacts the charging need, and to a very high degree on the charging behavior of the EV drivers. This could be shown by aggregating geographically simulated CS into two exemplary transformer substations according to charging needs: The highest peak reduction (50%) could simply be achieved by changing charging behavior both to slow charging and to evenly distributed charging with regards to the three different use cases (Charge@Home assumption) for the case of randomized starting SoC in scenario 4.

The outcome of the traffic simulation is in line with findings of previous studies that also compute the impact of EV charging loads under various conditions. Salah et al. (2015) conclude that a high EV market share can lead to overloads at specific locations on the grid. They evaluate that overloads are likely to occur when no coordination of EV charging exists. Furthermore, the results of the work by Clement-Nyns et al. (2010) show that power losses and voltage deviations are present at peak power levels. They also recommend some kind of coordinated charging to lower the impact of EV penetration. Finally, Alyousef et al. (2018) assessed the power quality of the grid under different power and load levels. In case of simultaneous and maximum EV charging, they forecast voltage drops and overloads of CS on the grid in the morning and evening. The authors implement coordinated charging and behavior changes with smart charging algorithms to lower peak levels and improve the power quality of the grid. These results of related work confirm the outcome of the traffic simulation of this paper.

Of course all this heavily depends on the way that charging use cases are geographically distributed onto the topology and how they are bundled in transformer substations. This leads to a threat to validity of the presented work: Driving data with regards to timing and trip purposes had to be transposed into geographical data, a process that is very sensitive to the underlying assumptions, in this case the randomization of trip assignments. However, we are convinced that randomization is the most transparent and meaningful way of doing this.

A second major issue is related to the necessity of consistency with the original MOP data: as driving distances are determined by the latter, it was not possible to physically aggregate "individual" charging points into CS with more than one charging point, so this had to be done virtually.

Conclusion

In this paper we assessed the impact from real driving data onto selected transformer substations of a real city through a dynamic simulation approach, assuming a 100% diffusion of electric engines. The intermediary focus was to create power profiles of CS that are located at home, work, and in public. This energy demand was computed in the microscopic traffic simulation SUMO for the geographical area of Mannheim. The simulated travel and charging behavior of EVs are based on the findings of the MOP survey. In total, 340 home, 466 work, and 593 public stations were modeled, and then further clustered into aggregated CS.

The main findings are that the impact of 100% EV diffusion cannot be stated in a static way, but depends on very local characteristics as the location and power of CS, characteristics originating from the cars themselves (efficiency and power draw) and the charging behavior of the EV drivers. The biggest peak reduction is achieved comparing the power profiles of scenario 2 (SoC-20% & MaxCharge) with scenario 3 (RandomSoc & Charge@Home) for transformer 2. The peak load of 132 kW in the afternoon at around 1 p.m. in scenario 2 drastically decreases to a peak load of only 66 kW, resulting in a 50% reduction for scenario 3. This shows the sensitivity of results to assumptions of initial SoC, but mostly it illustrates the power of behavior change.

In future work, among others the number of households will be scaled up to the real population. Finally, further progress in topics such as smart charging algorithms and different deployment of charging infrastructure are planned to be incorporated into the simulation. However, in order to assess the real grid issues arising from the additional electricity demand from a 100% EV diffusion, also the electricity supply side would be needed to be looked at in the simulation: For the case of a distribution grid characterized by distributed renewable energy sources such as solar and wind, it might be desirable to match EV based power demand with intermittent power supply as well as meeting the grid's capacity constraints. In all cases, changing the charging behavior plays a crucial role which, if carefully planned (Kacperski et al. 2022), can be very effective.

Combining EV power demand from real drivings and the real topology in a city as undertaken in the current work with the requirements of a changing grid, this is the main challenge to be dealt with in the future development of this stream of work.

Abbreviations

CS	Charging station
EV	Electric vehicle
ICE	Internal combustion engine
MOP	German Mobility Panel
OSM	OpenStreetMap
SoC	State of charge

SUMO	Simulation of Urban MObility
TraCI	Traffic control interface

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Author contributions
Both authors made contributions to the simulation design and implementation. SK has focused on framework and analysis, and she has guided the work; JWL has implemented the simulation. The authors have read and approved the final manuscript.

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Availability of data and materials
The MOP data underlying the driving and charging behaviour of this work are available from the MOP website at the Karlsruhe Institute of Technology/Germany (https://mobilitaetspanel.ifv.kit.edu/) upon request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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