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IDENTIFICATION OF SPATIAL ENERGY DEMAND SHIFT FLEXIBILITIES OF EV CHARGING ON REGIONAL LEVEL THROUGH AGENT-BASED SIMULATION

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ABSTRACT

Open access to electric vehicle charging session data is limited to a small selection provided by operators of mostly public or workplace chargers. This restriction poses a hurdle in research on regional energy demand shift flexibilities enabled by smart charging, since usage characteristics between different charging options remain hidden. In this paper, we present an agent-based simulation model with parameterizable availability and usage preferences of public and private charging infrastructure to access insights of charging behavior otherwise only visible through proprietary data. Thus, we enable utility operators to estimate spatial charging energy distribution and support the integration of renewable energy by showing potentials for smart charging. In a first application, we point out how increased access and use of private charging facilities can lead to additional energy demand in rural municipalities, which, in turn, leads to a lower grid load in urban centers.

1 INTRODUCTION

According to the U.S. Energy Information Administration (2024), 37% of the energy consumption in the United States by the end-use sector in 2023 was used for the transportation of people and goods, which was responsible for 39% of the United States CO_2 emissions in that year. The electrification of the transportation sector promises to reduce this impact. But, with the increasing number of electric vehicles (EVs), the electric grid load increases and the question of manageability of peak demands arises. This makes it difficult to guarantee the stability of the electric grid, as can be seen in the efforts made towards mitigating possible shortages or overloads caused by electromobility (e.g. Saldanha et al. 2024). Estimating and optimizing power demand profiles in the transportation sector has thus become a key topic.

For grid-compatible integration of electric mobility at the charging station level, several approaches have been developed and put into practice that incorporate peak shaving and valley filling (e.g. Spitzer et al. 2019). Modeling EV energy demand and simulating the use of the charging infrastructure is the method most frequently used to evaluate new concepts for the cost or emission-optimized operation of charging stations, as applied, for example, in Benz and Pruckner (2023). To achieve reliable predictions on future local charging energy demand, real data on existing traffic volumes, mobility demand, or completed charging sessions is used. However, the possibilities of predicting shifts in energy demand between different charging stations are limited if the charging infrastructure is not considered holistically (Xylia et al. 2025).

Adaptations in the charging behavior of EV drivers can occur at any time, especially when new charging options become available. In addition, it can be assumed that charging habits will continue to change, as electromobility is still in the ramp-up phase, and the adjustments for economic and ecological optimization have hardly lost momentum. We see untapped economic and ecological potential here and propose to use flexibilities in the spatial distribution of the charging energy demand to optimize EV charging from a regional perspective. To do so, we first need to identify correlations between daily activity locations of EV drivers and resulting charging behavior to be able to quantify the resulting possible variations in spatiotemporal energy demand in the second step. These can then be used to establish financial support for the targeted expansion of the charging infrastructure or to create incentives, for example, by promoting low-cost charging facilities in workplaces in order to better integrate electricity locally generated by solar photovoltaic systems. Yet, through the lack of region-wide access to charging session data, necessary correlations cannot be derived directly, and charging behavior needs to be modeled from a bottom-up perspective instead.

In this paper, we present a first version of a regional EV charging behavior simulation model (RCBSM) that reflects the charging behavior of individual light-duty EV drivers. It comprises individual activity patterns that include commute, education, shopping, or leisure activities. The access to private and public charging infrastructure, as well as the charging preferences of EV drivers, is made available as input parameters. Results are generated on the temporally and spatially resolved level for an entire metropolitan region. This wide spatial coverage makes it possible to examine the effects of commuting connections and the resulting charging characteristics and interactions in rural and urban areas in more detail. A holistic regional modeling of both private and public charging distinguishes our approach from other studies that focus on individual charging hubs or private or public charging infrastructure separately.

With our work, we contribute to the following research questions:

- What design constraints exist in modeling regional charging behavior and impact, and which methods are appropriate to maintain an efficient simulation of an increasing number of EV drivers?
- What potentials for grid-friendly, cost-optimal, or sustainable distribution of charging energy demand do availability of charging infrastructure and user charging preferences offer?

The remainder of this paper is structured as follows. In Section 2, we present existing work on simulating charging demand. Section 3 describes our regional charging behavior simulation model, together with a first application of which we highlight some results in Section 4. In Section 5, we conclude with a discussion of the results and an outlook on future work.

2 RELATED WORK

In order to identify an appropriate approach for modeling spatial and temporal EV charging behavior of an entire region, we give an overview of existing EV charging energy demand models including incorporated methods, their respective restrictions, and potentials.

Li et al. (2023) split EV charging models into three categories: temporal usage models, spatial usage models, and energy usage models. Temporal usage pattern models are built on time Markov chains, often in combination with Monte Carlo simulation (e.g. Bahmani et al. 2024), queueing (e.g. Pruckner et al. 2017) or machine learning (ML) (e.g. Kumar et al. 2024). They are used to determine usage profiles, charging energy demand, or theoretical optimization of utilization at specific individual charging locations or vehicle fleets. A detailed overview and evaluation of the work that applies ML is given by Yaghoubi et al. (2024). The authors emphasize the importance of collecting detailed data on EV charging behavior and demand profiles in order to set up ML models. Transferring these models to other charging locations thus requires expanding the data sources and retraining or fitting to the local conditions. This makes up-scaling them to an entire region, with the challenge of mostly inaccessible charging session data, complex.

For simulating spatial and energy usage, the agent-based modeling (ABM) approach finds application. In contrast to ML, research on ABM for charging demand promises adequate applicability for heterogeneous scenarios with a sparse database of charging processes. Instead of deriving statistics on usage by analyzing the target variable in real data, ABMs model the underlying behavior of individuals, which leads to the observed usage in a bottom-up way. In consequence, the quality of these models does not depend on the availability of proprietary charging sessions data. For a brief introduction on ABMs in the transport context, see, e.g. Huang et al. (2022). In traffic or transport simulations, ABMs map the mobility behavior of individuals based on activity chains, which can be derived from public mobility surveys or cell phone data covering large regions (Widhalm et al. 2015; Adenaw and Bachmeier 2022). Gravity models (Wilson 1967) based on open building data are then used to assign geographically allocated activity locations (Strobel and

Pruckner 2023). Calibration of generated trip chains can be achieved by incorporating origin-destination pairs as provided, e.g. through commuting figures (Hyman 1969).

Based on the generated mobility behavior at the agent level, the energy demand models can be implemented and used to simulate spatiotemporal charging behavior: Lee et al. (2020) use charging and travel data from 200 EVs in the United Kingdom to approximate charging demands and behavior patterns through an ABM. However, their model was limited to charging at home. In contrast, Jiang et al. (2024) implemented an ABM for charging behavior to predict charging demand on public chargers. They built their model on activity chains of individuals and show correlations between charging energy demand, daily activity patterns of the EV drivers, and the function of the chargers environment. Yang et al. (2018) also use an agent-based approach with a detailed charging behavior model and conclude that charging strategies can help mitigate negative impacts of EV charging on the electric grid. Nevertheless, their area of study is limited to an urban region and consumer preferences remain static. Focusing on open data such as household travel surveys or land use statistics, Straub et al. (2021) model activity-based mobility and the resulting distribution of charging energy at home chargers in Berlin, Germany. They point out the attractiveness of charging options in the city center and suggest considering combined charging strategies at work and in public in future studies.

In conclusion of this section, we identify the ABM approach as appropriate to simulate regional charging behavior on a limited session data basis in spatiotemporal resolution. We see potential to use ABMs to identify further possibilities in utilizing correlations between charging behavior and the resulting charging energy demand for grid friendly load shifting at the regional level. With this goal in mind, we implement a model of charging behavior that considers both private and publicly accessible charging infrastructure. As suggested by Straub et al. (2021) and in a review of EV charging research by Xylia et al. (2025), such a holistic view of existing charging options is crucial to derive realistic distributions of charging energy demand.

Based on the work listed above, we can underline a statement by McKinney et al. (2025) that previous models neglect the adaptation of electric mobility in rural regions. With our work, we address this gap and contribute to research on flexibilities in EV charging by investigating the differences between urban and rural areas on a regional level.

3 METHODOLOGY

In this section, we present our approach to model the charging behavior of EVs on the regional level. We give an overview of the simulation framework in which our new RCBSM is embedded. This includes architecture and data requirements, as well as input parameters, initialization, and charging behavior simulation logic of the RCBSM. At the end of the section, we describe the application of our model in a case study.

3.1 Framework Architecture

We chose an agent-based approach for the RCBSM, allowing us to modify a variety of parameters, which directly address the access of EV drivers to charging infrastructure and their charging preferences. As data are not available in comprehensive form for public and private charging sessions of an entire region, we focus on open data sources. Those cover mobility and commuting behavior, population and vehicle distribution, as well as locations and maximum charging powers of public chargers (see Section 3.2). We incorporate these data to infer the mobility demand of people living in the area under consideration from it. This mobility demand is then used in the RCBSM to derive spatiotemporal energy demand at the charging infrastructure and later in spatially aggregated form for simple interpretability. Accordingly, the simulation framework can be divided into three subcomponents - mobility demand generation, RCBSM and Aggregation and Analysis (see Figure 1).

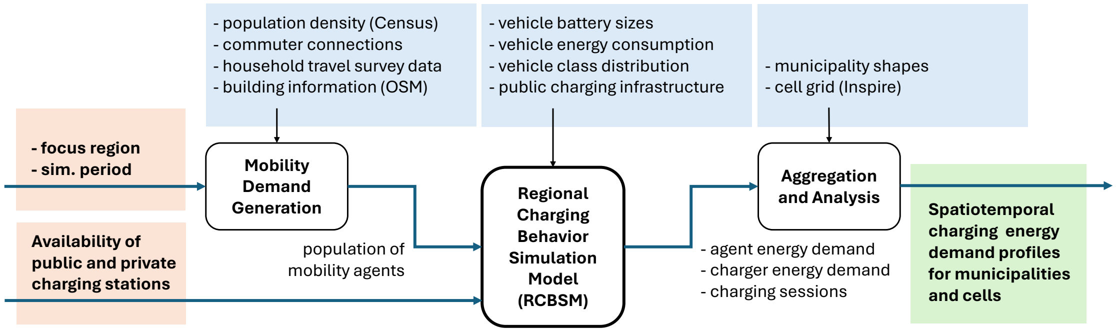


Figure 1: Simulation framework architecture including calibration data, model inputs and output.

3.1.1 Mobility Demand Generation

To obtain agents with realistic mobility behavior upon which individual charging behavior can be modeled, we use the OpenStreetMap Mobility Demand Generator (OMOD) developed and introduced by Strobel and Pruckner (2023). This open source tool uses non-proprietary data to synthesize a population of agents for a user-defined simulation period and region. Each agent is created with fixed places of residence and work and a mobility diary containing successive trips to activities described by location, type, and duration. For calibration, data from household surveys and commuter connections at the municipal level are included, so that the effects of regional mobility patterns on charging behavior can be investigated in the next step.

3.1.2 Regional Charging Behavior Simulation Model

The RCBSM, implemented in AnyLogic 8 (AnyLogic, Oakbrook Terrace, IL, USA), models the charging energy demand for each mobility agent and the resulting usage of the charging infrastructure. It comprises the allocation of EVs to the agents, the distribution of private and public charging infrastructure, and the simulation of the mobility and charging behavior itself. The model output is subdivided into statistics for agents, the charging infrastructure, and charging sessions. For efficiency reasons, we chose the discrete event simulation (DES) paradigm (for further information, see, e.g. Schruben and Yücesan 1993). More details on the RCBSM are described in Section 3.3.

3.1.3 Aggregation and Analysis

As the final step of the simulation framework, the charging energy demands in the area under consideration are aggregated and analyzed for specific subregions or charging locations. The object-oriented output of agents and chargers from the RCBSM leaves all options for temporal or spatial aggregation to the user.

3.2 Data Sources

The simulation framework is designed to be applied to any region on earth given a minimum set of non-proprietary input data. Here we give examples for Germany: The applied mobility demand generator OMOD is calibrated on household travel surveys (Nobis and Kuhnimhof 2018) and commuter connections at municipal level (Regionaldatenbank Deutschland 2023). The gravity-based destination choice model in OMOD uses building data from OpenStreetMap (2024) available on Geofabric (2024). The agent density distribution is based on Census Germany (2022) data. For a proper representation of the EV fleet, representatives for different classes of vehicles are taken from ADAC (2024). The respective net battery sizes and average consumptions included are necessary to model the charging frequency correctly. The vehicle class distribution in Germany is extracted from the registration figures in KBA (2024). A snapshot of the public charging infrastructure installed in Germany is provided by BDEW (2024).

3.3 The Regional Charging Behavior Simulation Model

3.3.1 Input Parameters

We designed the model in a way that enables its users to set the charging behavior of our mobility agents and their access to charging infrastructure as an input parameter. This allows possible changes in future development paths of EV adaptation to be handled and reduces dependencies on hardly accessible charging session data. Table 1 gives a summary of user-adjustable parameters for the RCBSM.

Table 1: Input parameters for the charging behavior simulation model.

Symbol	Definition
M	Set of municipalities
n_m	Count of simulated EVs in municipality m
a_W	Share of EV drivers with access to charging infrastructure at work
a_{SFH}	Share of EV drivers with access to home chargers of all those living in single family houses
a_{MFH}	Share of EV drivers with access to home chargers of all those living in multi family houses
f_{SOC}	Table function for plug-in probability at given state of charge
f_{range}	Table function for plug-in probability at given range sufficiency
P^+	Set of preferred charging locations of agents
P^-	Set of deprecated charging locations of agents
ϕ	Impact weighting factor of charging preferences on plug-in probability

3.3.2 Initial Distribution of EVs and Charging Infrastructure

The agents generated by OMOD correspond to the owners of EVs. For each municipality m in the area of consideration, given as a set of municipalities M, the number of simulated agents n_m is selected in such a way that the spatial distribution density of the EVs corresponds to the local registration figures taken from KBA (2024). The initial SOC of the EVs results directly from transient simulation runs.

The initial distribution of the charging infrastructure depends on the charger type: For home chargers, the type of residence (single-family or multi-family house) of the agent is first sampled for each agent. The probability for an agent to have a dedicated home charging option is then given by a_{SFH} and a_{MFH}. Agents with fixed workplace are assigned a semi-public charging option at their place of work with probability a_W. Public chargers are integrated using open data on installed charging stations, which include location, charging power capacity, and the count of available charging points per station.

3.3.3 Energy Demand for Mobility

The mobility behavior and the resulting energy demand of each agent are strongly related to its mobility diary, which is generated in the first component of the simulation framework and represented as a linked list of consecutive activities. The simulation steps through this list. Each activity is carried out for a certain time until the next activity starts. With the start of an activity, an event is scheduled, triggering the processing of the next event after the expiration of the dwell time at the current activity. Transit activities are triggered to reach the next activity locations. The model includes a light-weight mode choice model to decide whether an agent uses its EV when leaving home. The decision is made with knowledge of the mileage and the probability of taking the EV for a tour of that mileage derived from household travel surveys. For EV trips, the energy demand to cover the mileage is subtracted from the EVs buffered energy, leading to the desire to recharge at given time. For each agent, this process is repeated in parallel until the last element of its mobility diary is reached. Figure 2 illustrates this more clearly.

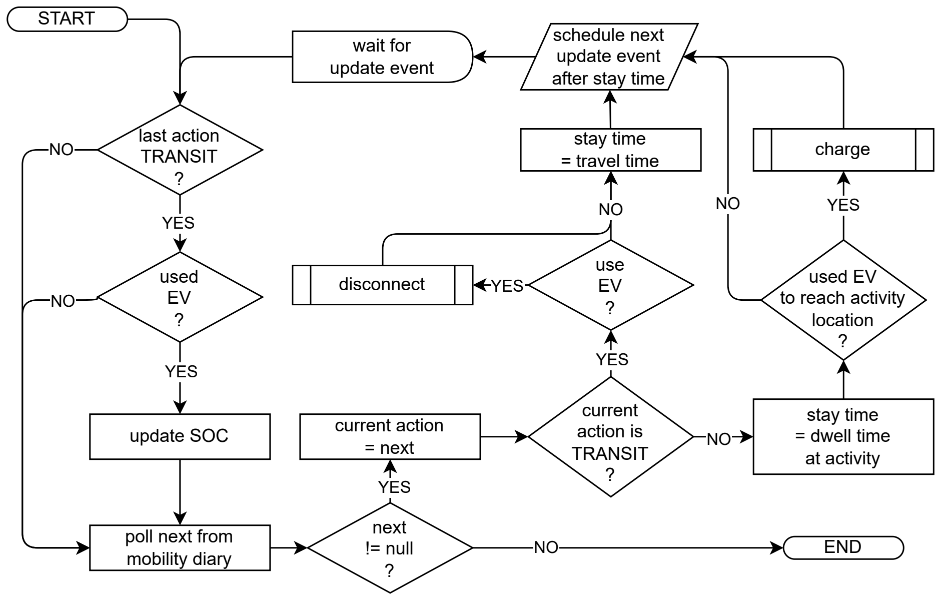


Figure 2: Flow chart of the agent activity processing.

3.3.4 Charging

Any time a mobility agent reaches a non-transit activity location by EV, it decides whether to charge or not. In Figure 2 this process is encapsulated in the box titled "charge". A charging process cannot be started when the agent is not using its EV to reach an activity. The charging process is started with an arrival at a non-transit activity location. To start a charging process, two conditions must be met: First, a charger must be available at the activity location, and second, the agent's desire to charge must be given. The latter describes the agent's charging behavior and is modeled in four subroutines. These are built on correlations between the current SOC of an EV or upcoming mobility demand of the agent and the probability to connect to charging infrastructure, based on the findings on charging behavior by Bollerslev et al. (2022) and Hipolito et al. (2022):

Plug-In Probability for Given State of Charge

This subroutine models the desire to charge, analogously to the typical behavior of refueling internal combustion engine cars. f_{SOC} is modeled as a function calculating a probability p_{SOC} of desiring a recharge based on the current SOC (see Figure 3a). The SOC of a vehicle is defined as the quotient of the current remaining buffered energy E_{rem} and the buffer size E_{max} of the vehicle battery (see 1).

$$SOC = \frac{E_{rem}}{E_{max}} \tag{1}$$

Plug-In Probability for Given Range Sufficiency

This subroutine models the desire of agents to be able to fulfill the upcoming trips without the need to recharge on the way. It is based on a table function f_{range} that returns the probability p_{range} to charge an EV depending on a range sufficiency ratio r which reflects what share of the EV's current SOC is consumed to cover the total mileage of upcoming trips (see Figure 3b) with r being calculated by

$$r = \frac{E_{req}}{E_{rem}}.$$

E_{req} describes the energy required for vehicle v with consumption c_v to complete upcoming trips S with distance d and is calculated as given in (2).

$$E_{req} = \sum_{s \in S} d_s \cdot c_v \tag{2}$$

Overall Charging Probability

Based on p_{SOC} and p_{range}, the overall base charging desire probability $p_{overall}$ is calculated as the counterprobability of the case in which an agent does not want to charge, neither according to SOC nor due to lack of range (see 3 and Figure 3c.) High values for p_{SOC} or p_{range} overrule lower individual probabilities and, thus, a more realistic modeling of urgent charging demand cases is achieved.

$$p_{overall} = 1 - ((1 - p_{SOC}) \cdot (1 - p_{range})) \tag{3}$$

Impact of Charging Preferences on the Plug-In Probability

This subroutine covers the behavior of EV owners who prefer charging their vehicle when carrying out a specific activity, e.g. any time an agent arrives at home or work. It is implemented as a power function to the upstream calculated overall charging probability $p_{overall}$ as given in (4).

$$p_{pref} = (p_{overall})^{f(P^+,P^-,l,\phi)} \tag{4}$$

$f(P^+,P^-,l,\phi)$ calculates an impact factor of an agent's preference to charge at the current location type l given the sets of P^+ and P^- and a parameterizable impact weight ϕ, calculated as

$$f(P^+,P^-,l,\phi) = \begin{cases} \frac{1}{\phi}, & \text{if } l \in P^+ \\ \phi, & \text{if } l \in P^- \\ 1, & \text{else.} \end{cases}$$

This routine increases the probability to charge at the current location, if the type of the location l is contained in the set of preferred charging locations P^+ and decreases it, respectively, if l is in P^-. In contrast to fixed charging rules, this approach respects the previously calculated charging necessity, e.g. due to low SOC and thus avoids a too strict rejection of charging, which would lead to an increased share of agents with unsatisfied charging energy demand (negative SOC).

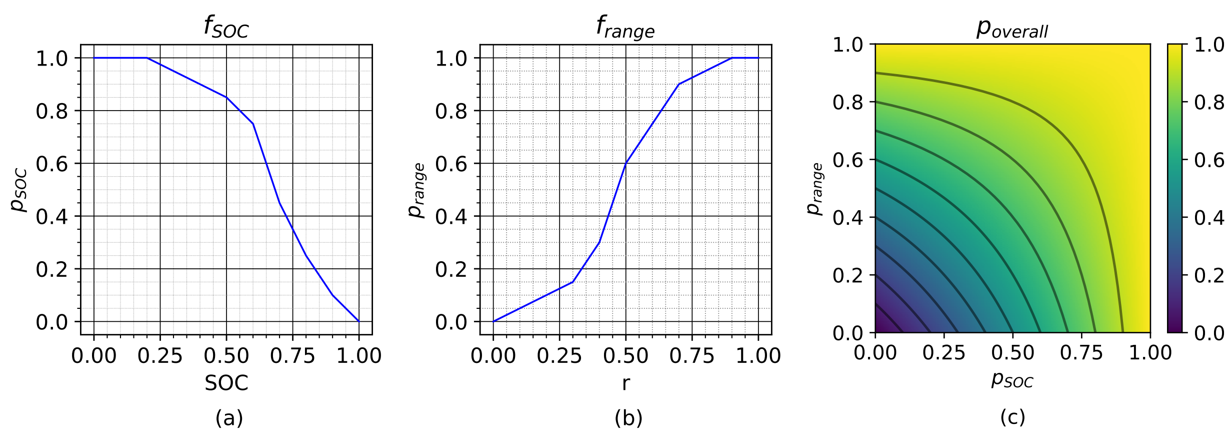


Figure 3: Table functions f_{SOC} (a) and f_{range} (b) together with the overall charging probability $p_{overall}$ (c).

3.3.5 Model Outputs

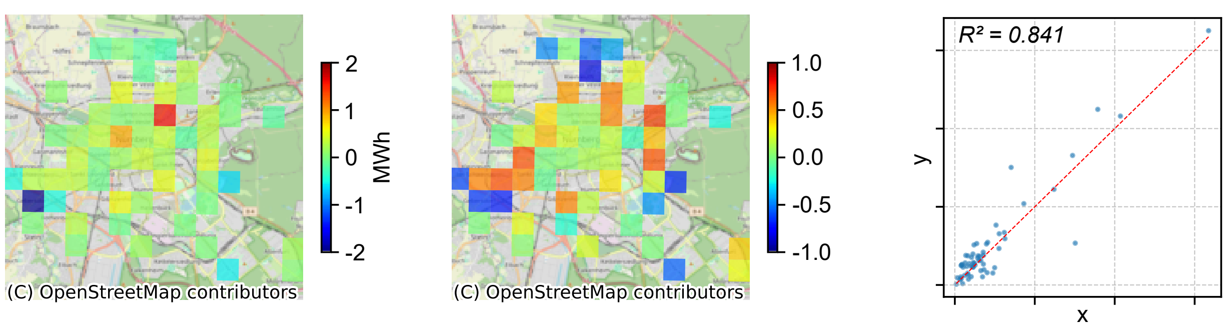
The results of the RCBSM are exported to three files. The first one summarizes for each mobility agent its fixed home and work location as geo-coordinates, access to private charging infrastructure, mileage, total charged energy, battery buffer size, and state-of-charge profiles (%) in adjustable time resolution. The second lists geo-coordinates, types (HOME, WORK, PUBLIC $\leq$22 kW, PUBLIC $>$ 22 kW), and usage profiles (kW) in adjustable time resolution of public and private charging stations in the area of consideration. In the third output file, all simulated charging sessions carried out at the charging infrastructure in the area of consideration are recorded. These comprise connection and charging time, charging power, delivered and consumed energy, as well as reference to the agent undertaking the charging session and the charging station used. The information contained in the output files allow deep insights into the simulated charging behavior and the resulting spatial and temporal energy demands. This makes it possible to investigate shifts in demand between charging locations or to estimate load profiles for certain subregions.

3.3.6 Validation

For the model validation, we firstly compared the shares of the total charged energy at the different charging locations from our model with literature values. Secondly, we validated the energy charged at selected public charging infrastructure in our case study region using exclusive charging session data from the local energy provider. The validation data sets were masked to the charging stations contained in both datasets before aggregation. An example of the validation results for the total energy charged at public chargers in the city of Nuremberg is given in Figure 4. Colored cells are those with relevant chargers. Absolute energy values are masked to comply with privacy policies. Looking at relative deviations (Figure 4b) in energy demand for 1km x 1km cells, we see a good fit of the model output to the real charged energy for the city center. The deviations of the relative demand in the suburbs and rural areas are higher, since there we find smaller absolute demands for which smaller deviations have a higher impact on the relative scale. The real charging energy demands for urban and rural regions are reflected with an $R^2 = 0.841$ (Figure 4a and c).

Combining the overall shares of charging energy demand of the different charging locations and the spatial validation of charged energy at public chargers, we achieve a reasonable certainty about the correct dimension of total energy quantities in our model.

The validation of our model was possible with access to proprietary data on public charging sessions. On the other hand, charging session data at private locations is mostly not available - neither for research nor the energy providers themselves. But, with our model, we provide first estimates and sensitivities for these, yet veiled energy demands.



(a) Absolute deviations (b) Relative deviations (c) Real (x) vs. sim (y)

Figure 4: Spatial validation of the modeled charging energy demand at public chargers.

3.4 Application

In a first application of our RCBSM we have a closer look on the impact of charger availability and charging preferences on energy demands at different charging locations, differentiated by home, workplace and public in spatial resolution for rural and urban municipalities. We apply our model in the European Metropolitan Region of Nuremberg (EMN) for the year 2023. The EMN is an approximately 22,000 km² region with around 3.6 million inhabitants in the north of the federal state of Bavaria, Germany (EMN 2024). It is characterized by a heterogeneous settlement structure around the centrally located city of Nuremberg (almost 550,000 inhabitants) with several smaller towns and strongly rural subregions. In January 2023, about 45,700 EVs were registered by owners living in the EMN (KBA 2024). In order to take into account the influence of EV drivers living outside the EMN on the use of the charging infrastructure in the region under consideration, the buffer zone for generating mobility agents was set to 40km. This resulted in a total of approximately 72,000 simulated EVs entering the EMN for activities during the simulation. Based on a publicly available data source, provided by BDEW (2024), we included all public chargers registered in Germany by January 2023, which contained 2038 normal charging points ($\leq$ 22kW charging power) and 560 fast charging points ($>$ 22kW) within the EMN region.

For each scenario combination described below, we performed multiple simulation runs, each covering a simulation period of one average week of a year from Monday to Sunday, excluding a one-day transient phase at the start and the end of the simulation. The simulation time step is one minute. All scenarios were simulated using the same set of agents, generated by OMOD in advance of the charging simulation to maintain comparability.

3.4.1 Scenario Definition and Setup

To give an estimate of the impact of changed charging behavior or access to private chargers, we performed a parameter variation on these variables. The previously described numbers of EVs and public chargers are kept static, while charging preferences and access to home chargers in single (a_{SFH}) and multi family (a_{MFH}) houses and chargers at workplaces (a_W) is varied. An overview of the scenario settings for changed charging preferences is given in Table 2. The investigated scenarios for changed access to private charging infrastructure together with resulting counts of simulated home (c_{HOME}) and workplace chargers (c_{WORK}) inside the EMN region are shown in Table 3. We chose rather extreme scenarios to explore the boundaries of the value range for possible development paths. For all scenarios, the simulation period is one week. The simulation runs were performed on a standard laptop (11th Gen. Intel i7 @ 2.80 GHz, 16 GB RAM) within a simulation runtime of 100-120 seconds for the described application.

Table 2: Investigated charging preference settings.

Name	P^+	P^-	Description
$P0$	$\{\}$	$\{\}$	Baseline without specific charging preferences.
PH	$\{HOME\}$	$\{WORK, PUBLIC\}$	Scenario with increased preference for home charging. Preferences for work and public charging are reduced.
PW	$\{WORK\}$	$\{PUBLIC\}$	Scenario with increased preference for work charging. Preferences for public charging is reduced.

Table 3: Investigated changes in access to home (left) and workplace chargers (right).

Name	a_{SFH}	a_{MFH}	c_{HOME}
$HOME^0$	90 %	55 %	36,876
$HOME^+$	90 %	90 %	41,125
$HOME^-$	65 %	35 %	26,017

Name	a_W	c_{WORK}
$WORK^0$	50 %	20,007
$WORK^+$	90 %	36,142
$WORK^-$	10 %	4,055

4 RESULTS

The results of our parameter variation are given as mean values of multiple runs, whereby the deviations of the runs are negligible. Looking at scenarios with varied charging preferences (Figure 5), spatial shift potentials are revealed by making use of charging flexibilities. For *PH* and *PW* we see that significant shifts of charging electricity demand to home charging stations (+ 34 % / + 20 %) are possible in both rural and urban areas. To compensate for this, the use of slow public charging stations is declining.

Figure 7 shows that decreases caused by shifts towards home charging mainly appear in urban areas: As an example, for the city of Nuremberg (dark blue area in the center) the simulation of the *PH* scenario results in 70 MWh less charging energy demand compared to *P*0. For surrounding municipalities, on the other hand, we identify an increase of up to 3.5 MWh. Similar results for the *PW* scenario let us infer that incentivizing private charging can help reduce the load on the electrical grid in city centers.

Figure 6 summarizes energy demands differentiated by charging location type for all simulated scenarios. The values are given relative to scenario $P0\ HOME^0\ WORK^0$. It can be seen that the expansion of private charging infrastructure has an impact on its usage even without adjusting charging preferences (*P*0): Additional charging infrastructure in apartment buildings ($HOME^+$) could lead to an increased home charging demand of 11 % (170 MWh). Expansion at workplaces would have a proportional amplifying effect (+79 % (135 MWh) for +80 % chargers). Promotion of workplace charging (*PW*) in combination with expanded workplace charging options offers very strong potential for load shifting towards more charging there: Our simulations show for $PW + WORK^+$ an increase in charging energy demand at workplace chargers of over 270 % (460 MWh) compared to an access level of 50 %, even without a reduction in home charging options. We point out to the outstanding potential for photovoltaic electricity integration there.

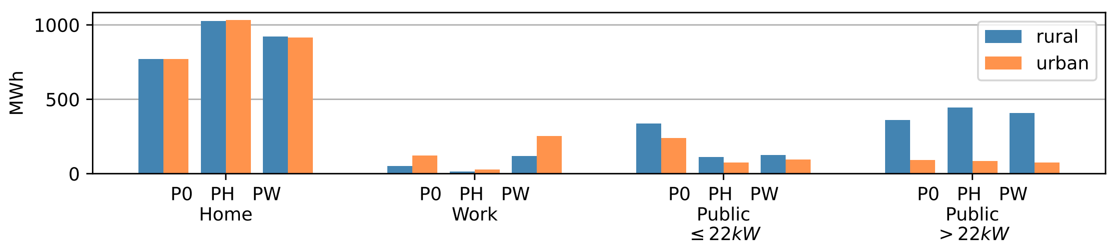


Figure 5: Cumulated energy demand for charging sessions in the EMN by charging location for rural and urban municipalities for $HOME^0$ and $WORK^0$ (access to home and work chargers remains unchanged).

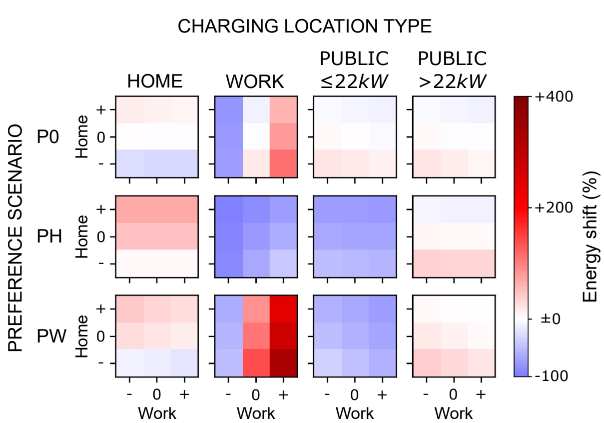


Figure 6: Demand shift between charging locations relative to $P0\ HOME^0\ WORK^0$ for all scenarios.

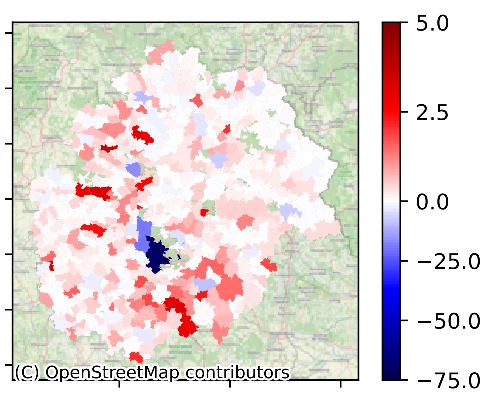


Figure 7: Simulated energy demand shift for EMN municipalities ($PH\ HOME^0\ WORK^0$).

5 CONCLUSION AND FUTURE WORK

Utility operators lack reliable information on the usage of the private charging infrastructure and estimates of the resulting amount of charging energy demand there. Simulations can provide valuable information on the spatial distribution of the total demand for charging energy and help to derive comprehensive potentials for the grid-supportive integration of electromobility. In this article, we introduced RCBSM, a simulation model that addresses this problem by mapping the spatiotemporal distribution of charging energy demand of private and public charging infrastructure at the regional level. It allows users to vary difficult-to-observe variables such as access to private charging infrastructure and personal preferences for the use of charging infrastructure. In a first application in the European Metropolitan Region of Nuremberg, we show the influence of user behavior and access to charging infrastructure on the spatial demand for charging energy on a cross-municipal scale. Corresponding potential for the promotion and expansion of charging infrastructure in order to contribute to more sustainable electric mobility is identified. The approach of a hybrid agent-based discrete event simulation serves to mitigate the restrictions caused by limited access to charging session data and also enables modelers to expand the focus of research on electromobility adaptation beyond the boundaries of individual charging parks to a regional level.

In future research, we will apply our model for further research on energy demand shift potential, especially in the case of non-homogeneous expansion of charging infrastructure. In addition, optimization of charging behavior on agent level towards improved economy and ecology lies in focus to better quantify flexibilities and ultimately be able to use them for improved integration of renewable energies.

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