Spatial and Temporal Charging Infrastructure Planning Using Discrete Event Simulation

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ABSTRACT

The switch from gasoline-powered vehicles to electric vehicles (EVs) is an important step to reduce greenhouse gas emissions. To this end, many European countries announced EV stock targets, e.g., Germany aims to have one million EVs on the roads by 2020. To achieve these goals and to handle the range limitation of EVs, a widespread publicly accessible charging infrastructure is needed. This paper provides a dynamic spatial and temporal simulation model for the building of charging infrastructure on a municipality scale. We evaluate empirical data about the timely utilization of different charging stations in the German federal state of Bavaria. This data is used to derive empirical models for the start time and duration of charging events as well as the popularity of charging stations. We develop a lightweight discrete event simulation model which can be used to investigate different expansion strategies, e.g., based on the load of charging stations or the number of successful and failed charging attempts. We show the applicability of our model using the German federal state of Bavaria as a use case.

Keywords

Discrete Event Simulation; Charging Infrastructure Planning; Electric Vehicles; Electromobility; Charging stations

1. INTRODUCTION

According to the Global EV Outlook 2016 [1] fourteen countries have announced EV stock targets, aiming to bring thirteen million EVs on the road in the near future. For instance, the German government aims to have one million EVs on German roads by the end of 2020. One major challenge for achieving these numbers is overcoming the main disadvantage of EVs, namely their limited range of approximately 150 km [8]. One way to mitigate this shortcoming is to provide a widespread, publicly accessible charging infrastructure.

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According to the Progress Report and Recommendations of Charging Infrastructure for Electric Vehicles in Germany 2015 [7], there will be a need of about 16,000 charging stations by 2020. In more details, 5,700 additional fast charging points and 10,000 normal AC charging stations (meaning 20,000 additional normal charging points) will be needed until 2020. In the federal state of Bavaria alone (consisting of 71 administrative districts and 25 independent cities) there are plans to build as many as 7,000 publicly accessible charging stations [2]. There exist various programs to meet these requirements [7], however, at this point it is unclear where and when new charging stations should be built. Stakeholders and decision makers could benefit from reliable predictions based on detailed statistics about the utilization of today's charging infrastructure.

In order to provide such predictions and recommendations, we develop a novel methodology for charging infrastructure planning using empirical data and discrete event simulation.[1] We evaluate the available empirical data including charging information about 394 charging stations in Bavaria over a four month period. This information is used to describe charging events with regard to their start time and duration. Under the additional consideration of an exponential growth of EVs until the end of 2020, we model the increasing number of charging events on publicly accessible charging stations. We define different output parameters such as the probability of successful charging attempts, the utilization of a charging station, as well as a theoretical waiting time in order to assess different scenarios regarding the expansion of charging infrastructure. Given different expansion strategies, we derive a spatial and temporal expansion schedule for each subregion in the federal state.

The remainder of the paper is organized as follows. In Section 2 we give an overview of related work in the field of charging infrastructure planning. We explain our system model in Section 3, followed by Section 4 where we describe the developed methodology, input modeling and the implementation of our discrete event simulation model. In Section 5 we present results for the use case study carried out using data for the federal state of Bavaria. Section 6 provides a discussion about our model and Section 7 concludes the paper with a short summary and an outlook on future work.

[1] The empirical data was provided by CIRRANTiC GmbH, a company which provides enhanced data streams to users and information management tools for EV infrastructure.

2. RELATED WORK

There exist several publications on charging infrastructure planning on an abstract level. For instance, Germany's report on Charging Infrastructure for Electric Vehicles [7] provides an overview of the current status of Germany's charging infrastructure. The authors mentioned that the expansion in normal charging infrastructure has been slowing since 2012 due to poor cost-efficiency, whereas the ramp-up of EVs is much more pronounced. Nevertheless, it is important that the number of publicly accessible charging stations grows with the number of EVs on German roads. This fact is also mentioned in a position paper by the Bavarian state government and Bavarian car manufacturers [2]. Although in Germany's report at least a rough schedule for expansion in charging infrastructure is given, only the Bavarian position paper provides a hard target number of 7,000 in total. Detailed schedules and spatial distributions of the presented total number of charging stations is not available. This is a major concern for stakeholders and infrastructure planners since they don't know where and when the expansion of new charging stations is necessary.

Literature pertaining to charging infrastructure planning relevant to the subject of this paper is also focused on spatial and temporal distribution.

Wirges [11] developed detailed models for charging infrastructure planning. He refines the planning not only for regions but also for the street level and presented different application areas of his model. In a second step, he developed a simulation model for the long-term development (until 2020) of charging infrastructure based on the increasing number of EVs, calculated quotas of charging points per EV and also inter-municipal commuter data for the German city of Stuttgart. His simulation results showed that only 1.2 % of all charging points were public charging points. Brost et al. [3] developed a site selection model for electric charging infrastructure based on origin-and-destination traffic generation, different user groups, and their trip behavior. Further input parameters include the zone-specific points of interest (POI) and information with regard to the duration of stay. Based on a vehicle ownership model and current charging infrastructure, the number of possible charging cycles can be determined. The results can be used by local planners to make micro-location plans for expansion of the charging infrastructure. Both publications have in common that they don't use empirical data for the modeling of charging events.

In Bi et al. [9] the authors developed an optimal charging station deployment model under the consideration of different charging behavior. To this end, they used an agent-based sub-microscopic city-scale traffic simulation which allows the investigation of different charging behavior under the assumption that charging stations are placed at existing gas stations. Results show that charging behavior has an influence on the charging infrastructure of the city-state Singapore. However, a charging infrastructure plan from a temporal perspective is not given.

Authors of [10] investigate where the state of charge would reach a critical level and, from that, they infer candidate locations for charging stations. They also took into account parking lots and driving behavior. The optimal placement of charging stations is also addressed in Lam et al. [5]. They define an optimization problem by finding the best locations to construct charging stations in a city by solving the EV charging station placement problem. The authors are focused on the complexity of these kinds of problems and propose four different solution methods. A temporal plan of charging stations placement is not given in detail.

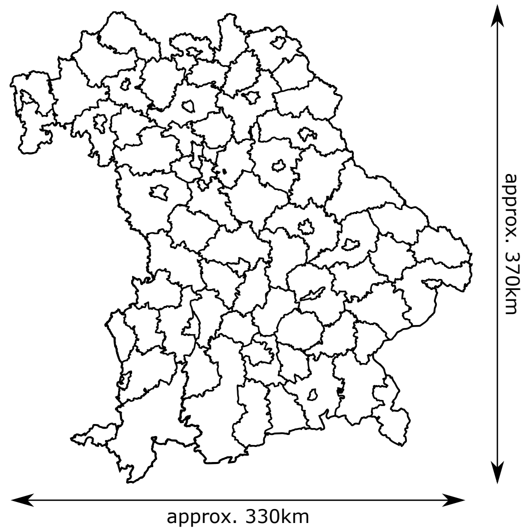


Figure 1: Scale of simulation: map of Bavaria, Germany with municipality borders.

There also exist several publications investigating the effect of electromobility on the power grid. In Dharmakeerthi et al. [4] the authors applied a particle swarm optimization-based approach for the planning of EV infrastructure on a distribution feeder level. They suggest to promote public charging stations in order to reduce electricity network upgrade requirements to accommodate EV charging on low voltage networks.

The idea of this work is to present a lightweight discrete event simulation model for the spatial and temporal charging infrastructure planning based on empirical data about the utilization of the existing charging infrastructure and the ramp-up of EVs as an input. Our model allows to derive detailed spatial and temporal expansion plans for different regions. The applicability of our model is shown for the German federal state of Bavaria. However, our approach can be applied to any other region worldwide as long as sufficient input data is available.

3. SYSTEM MODEL

The goal of the simulation is to give spatial and temporal recommendations for the building of charging infrastructure on the municipality scale. Figure 1 provides a visual reference for the scale of the simulation. It shows the German federal state of Bavaria with municipality borders. In total, Bavaria is divided in 96 municipalities. The outcome of the simulation is a recommendation for when to build charging stations at a temporal resolution of one week and a spatial resolution on the municipality level.

To achieve this, we have to make several assumptions. First, we want to abstract away from microscopic driver models, charging behavior, and mobility altogether by utilizing empirical data collected by today's charging stations. Creating realistic microscopic traffic demand, traffic assignments, and psychological driver models, combined with specific local features of the vicinity of a charging station is infeasible at the scale of a federal state spanning more than 70,000 km^2. By utilizing existing real-world charging data, we bypass the necessity for these complex and possibly inaccurate models, as the empirical data already inherently includes the results that would be obtained using these models. The empirical data used in this study includes the number of electric vehicles per municipality, the number and location of charging stations, as well as detailed information about *charging events* in the federal state of Bavaria. We define a charging event as the triple of the charging station, the start time, and the charging duration.

From the empirical distribution of charging events, we derive charging events in the simulation. This means we do not model state of charge and trip distances, we assume that all charging events are of opportunistic nature, that is, if a charging station is occupied, the driver will not wait. Each charging station is assumed to have two outlets. As the charging duration is derived from real-world data, we do not model charging speeds. We assume that the charging stations about which we do not have empirical data behave the same as the ones we do have data about. This means that we assume charging stations about which we have data to be representative. With communication capabilities added to more and more charging stations, this assumption naturally becomes less critical.

For the building of new charging stations, we assume that charging stations can be built instantly. We do not consider the profitability of publicly accessible charging stations, nor do we assume that there will be a different distribution of charging station popularity after new ones are added. This is done to keep our model lightweight and to avoid unjustified assumptions. We also do not consider restrictions regarding the underlying power system. The main reason for this is that we do not recommend the exact position where the stations should be built. Such recommendations would naturally have to consider the power grid.

As for the scenario, we assume that a total number of 200,000 electric vehicles in Bavaria will be reached by the end of 2020. We assume the distribution of electric vehicles among the different municipalities to be the same over the simulation time.

4. METHODOLOGY

In this section we describe the applied methodology. First, we present the modeling of input parameters, including the progress of the number of EVs over time and the implemented expansion strategies for charging infrastructure. Subsequently, we briefly discuss the development of the discrete event simulation model.

An overview of our simulation is given in Figure 2. A large part of the input consists of empirical data that has to be processed and prepared to be used in the simulation environment. Additionally, we define different expansion strategies for the building of charging infrastructure.

In order to account for incomplete and missing data, we make use of the empirical distribution of the input data. Based on this, the discrete event simulation will derive charging events (start time and duration in the resolution of minutes), add infrastructure on a weekly basis, and also gradually increase the numbers of electric vehicles in the system. Based on the success rate, the load of the charging stations, and the expansion strategy, we can then give recommendations for the building of charging infrastructure.

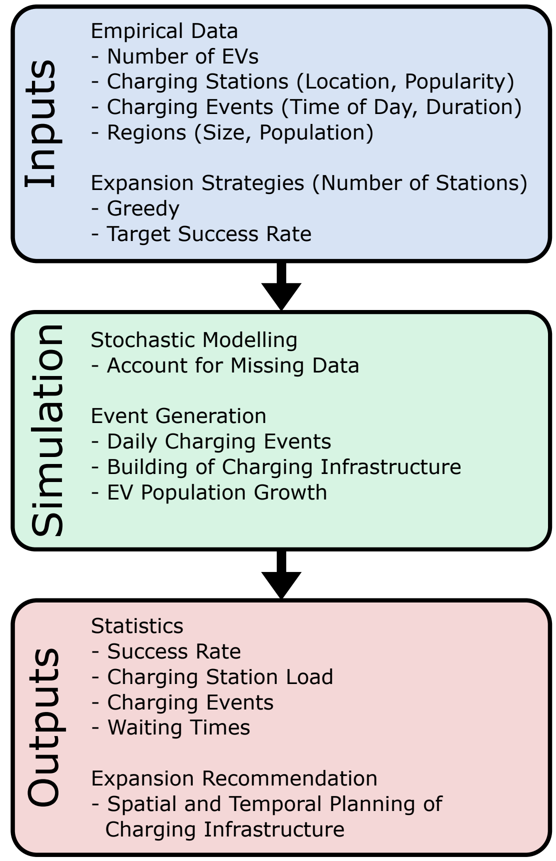


Figure 2: Inputs and outputs of the developed simulation engine.

4.1 Input Modeling

4.1.1 Regions

Input data for each municipality in the federal state of Bavaria includes the number of electric vehicles, the population, the area size, and the type of municipality (e.g., city, town, rural, etc.). For some of the investigated areas, there was no available information about the number of charging events. Developing a linear model, based on population, area size, and number of EVs to determine the number of daily charging events per region was not possible ($R^2 \approx 0.5$). We conclude that at this rather early stage of electric vehicle market introduction, local characteristics of municipalities (e.g., the presence of a car manufacturer) have a higher impact on the EV market share of a region, making the number of daily charging events hard to predict. We therefore decided to apply hierarchical clustering, and arrived at 15 different clusters for the 96 municipalities. We validated the clustering result by again applying a linear model to determine the cluster for each region and arrived at an R^2 value of 0.9 and higher. This means that some regions have common characteristics in terms of EVs, population and daily charging events. Others, even though they are the same type of municipality, are considerably different. We assume that regions belonging to the same cluster will share common characteristics in terms of charging events, allowing us to also model regions where only limited empirical data is available.

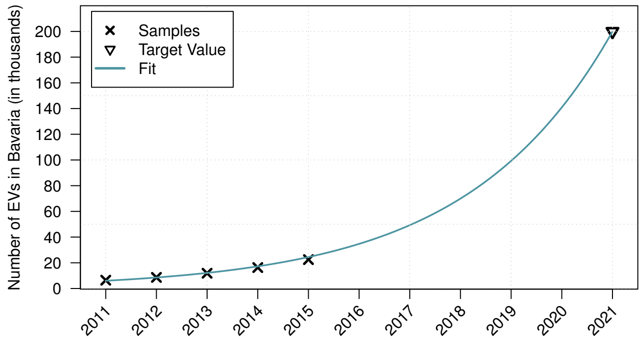


Figure 3: Development of the number of EVs in Bavaria from 2011 to 2021.

4.1.2 *Modeling the Number of EVs*

As the German government aims to have one million EVs on the road by the end of 2020 [1], we derive that, based on today's share of vehicles, Bavaria will have approximately 200,000 EVs. Under consideration of the historical number of EV registrations from 2011 to 2015, we fit an exponential increase for EVs (see also [6]). The fit is depicted in Figure 3 and given by the function

$$EV(t) = 6,027 \cdot \exp\left(0.3502 \cdot (t - 2012)\right), \tag{1}$$

wherein year $t \geq 2012$. In order to distribute the number of EVs across different regions (administrative districts and independent cities) in Bavaria, we use official statistics of vehicle registration authorities and derive a distribution factor $\beta_i \in (0, 1)$ for each region i. The development of EVs in region i is given by

$$EV_i(t) = \beta_i \cdot EV(t). \tag{2}$$

Thereby, we assume that the share of EVs within each region with regard to the total number of EVs to be constant over the next years.

4.1.3 *Modeling of Charging Stations*

As of today, there exist approximately 1,250 charging stations in Bavaria, however, only 394 of them have a back-end connection that allows to collect statistics. These charging stations store information about each charging event, that is, the start time and the duration. For each region we derived the following information for a period of four months:

- Histogram over start times of charging events in a fifteen minute resolution
- Histogram over duration of charging events in a fifteen minute resolution
- Histogram over popularity of charging stations

An example histogram over the start time of charging events is shown in Figure 4a for a small city in Bavaria. We observed similar features for almost all charging stations. It can be seen that most of the charging events on publicly accessible charging stations take place between 08:00 and 18:30. The peak at about 17:00 can be explained as this is a common time to finish work in Germany.

In Figure 4b the histogram for the duration of charging events is given. Most of the charging events last between fifteen and ninety minutes, mainly caused by people charging their vehicle while shopping. Longer charging durations could be observed at long-term parking lots and locations where people change to public transport. We also observe that vehicles occupying a charging station for over 24 hours is not uncommon.

Figure 5 depicts an example histogram for the popularity of charging stations, showing that two charging stations are considerably more popular than the remaining eleven. These two stations experience more charging events than the rest of the back-end stations in this municipality combined. This is similar to what we observed for many regions, meaning there is no gradually decreasing popularity but rather only two types of charging stations: popular and considerably less popular. In this example, the number of charging stations with a back-end connection was 13, the overall number of stations in this region, however, was 38. Assuming the missing charging stations behave similar to the ones with a back-end connection, we add them based on the existing popularity distribution. This is a strong assumption, especially when the number of back-end charging stations is low. We make equal-probability random selections between charging stations with back-end connection (cf. charging station ID in Figure 5), multiply the given number of charging events with a Gaussian distributed parameter ($\mu = 0, \sigma = 0.15$), and add the new charging station to the histogram. Figure 5a shows the histogram over the popularity of charging stations after the expansion of the original histogram to the total number of charging stations within this region.

4.1.4 *Number of daily charging events*

From the total number of charging events in a certain region i, we derive the mean number of daily charging events ϕCE_i^{day} by dividing the total number of charging events by the number of days within the four month period. In order to determine the number of daily charging events within a certain region we have also to consider charging events that occurred on charging stations without back-end connection. We assume the same utilization of charging stations without back-end connection using the ratio between charging station in total CS_i^{total} and with back-end connection CS_i^{conn}. The utilization depends also on the number of EVs, meaning we also take into account the ratio of the number of EVs at the simulation start time $EV_i(0)$ and the number of EVs $EV_i(t)$ at time t.

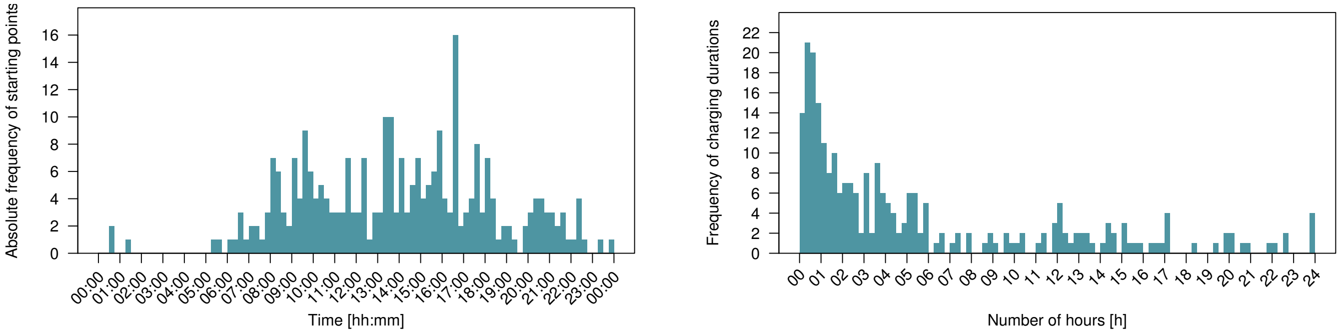
For a certain region i the number of daily charging events $CE_i(t)$ is given by

$$CE_i(t) = \phi CE_i^{\text{day}} \cdot \frac{CS_i^{\text{total}}}{CS_i^{\text{conn}}} \cdot \frac{EV_i(t)}{EV_i(0)}. \tag{3}$$

As in the real world the number of daily charging events is not a deterministic number we also consider stochastic influences modeled by a Gaussian distributed parameter α ($\mu = 0, \sigma = 0.15$). Thus, further influences such as holidays, seasons or special events (e.g., sporting events) can be described. We acknowledge that, ideally, this should be derived from the empirical data as well, however, the low sample size of charging events for public holidays and other special occasions did not allow us to draw conclusions.

The modeled number of daily charging events is given by

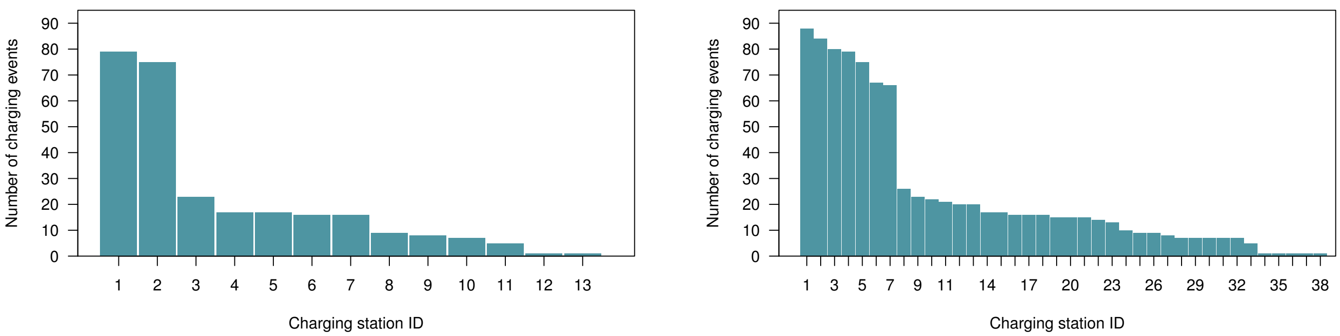
$$\widehat{CE}_i(t) = (1 + \alpha) \cdot CE_i(t). \tag{4}$$



(a) Example histogram for the distribution of starting points of charging events.

(b) Example histogram for the distribution of duration of charging events.

Figure 4: Example charging events recorded for a small town.



(a) Example histogram for popularity of charging stations within a small city in Bavaria.

(b) Example histogram of popularity of charging stations including charging stations without internet connection.

Figure 5: Empirical and synthetic charging station popularity for a small city.

4.1.5 Expansion strategies for charging infrastructure

The Bavarian state government aims to have up to 7,000 publicly accessible charging stations installed by the end of 2020. For the expansion of charging infrastructure we consider two different expansion strategies: *Success* and *Target*. In the simulation, the decision to build new charging stations is made on a weekly basis. In order to catch up with the exponential growth of EVs and the fast increasing charging station demand, we double the number of newly built charging stations per region if this region was already selected for expansion in the previous week.

The first expansion strategy, denoted as *Success*, is based on the percentage of successful charging events (cf. Equation 5). We treat every region in Bavaria as stand-alone, meaning that the number of new charging stations is independent from the number of new charging stations in another region. If the percentage of successful charging events drops under a threshold τ (e.g., under 0.95), then new charging stations will be constructed in this region. The overall number of built stations in the scenario then solely depends on τ, i.e., no upper bound for the number of new charging stations is considered. In Algorithm 1 the principal idea of this expansion strategy is shown. When a new station is added to a region, its popularity will be determined in the same manner as non-back-end stations are added (cf. Subsection 4.1.3).

The second expansion strategy, denoted as *Target*, assumes that the number of charging stations should also grow exponentially to serve the exponentially growing number of EVs (cf. Figure 3). Based on this function, we determine the number of available charging stations per week. Compared to the *Success* strategy, *Target* is more of a centralized approach, meaning that there is a total weekly limit of charging stations which can be built. To this end, we sort all regions within the simulated area by the percentage of successful charging events in an ascending order. Then we add charging stations until all available stations have been assigned a region. To catch up with increasing demand, the number of newly built charging stations is doubled for regions that already experienced an expansion in the week before. The working principle of *Target* is given in Algorithm 2

The main difference between the two expansion strategies lies within what they try to achieve. *Success* gives information about how many charging stations are required to achieve a certain success probability, whereas *Target* distributes a predetermined number of charging stations in a manner so that the average success probability between regions is maximized.

Algorithm 1: *Success* expansion strategy.

Definitions:
t The current week
$p_i^{\mathrm{succ}}(\mathrm{t})$ The percentage of successful charging attempts in region i during week t
$\mathrm{new}_i(t)$ The number of stations to be built in region i in week t
τ The threshold for the construction of new stations

foreach *region* i **do**
  if $(p_i^{succ}(t-1) < \tau)$ **then**
    $\mathrm{new}_i(t) = 2^{\mathrm{new}_i(t-1)}$
  else
    $\mathrm{new}_i(t) = 0$
  end
  Build $\mathrm{new}_i(t)$ charging stations in region i
end

4.2 Simulation Model

The simulations were conducted using the discrete-event simulator OMNeT++, a component-based C++ simulation library and framework. It provided the event scheduling engine and the required statistical tools.

4.2.1 Description of a single charging event

The exponential growth of EVs combined with the input distributions based on the empirical data determines the number of charging events per day per region. For each region, the simulation maintains three distributions, i.e, one over the start times, one for the charging durations, and one for the popularity of stations.

The simulation will schedule an event every day at 0:00 to determine the charging events for the next day. Based on the three stored distributions per region, we draw $n = 3 \cdot \widehat{CE}_i(t)$ random numbers. Each triple of start time, duration, and charging station describe a charging event. The events are sorted by start time and processed one by one to determine whether a charging attempt was successful. If there is an outlet available at the randomly determined charging station, then this outlet is set to occupied for the duration. The charging event is set to successful. Should there be no available outlet for a charging event, then we define this charging event to be failed.

For an example region of Bavaria an excerpt of an event list sorted in chronological order regarding starting times is given in Table 1. It can be seen that most of the charging events are successful. However, charging events 11 and 14 failed because both outlets of the target charging stations were already occupied by earlier events.

4.2.2 Output measures

Simulating at charging event level allows us to derive various output measures to assess the overall performance of the charging infrastructure. Let $\#CE^{\mathrm{succesful}}$ be the number of all successful charging events, and $\#CE^{\mathrm{total}}$ the total number of all events, then the overall success probability $p^{\mathrm{succ}}(t)$ can be given as:

$$p^{\mathrm{succ}}(t) = \frac{\#CE^{\mathrm{successful}}(t)}{\#CE^{\mathrm{total}}(t)} \tag{5}$$

Algorithm 2: *Target* expansion strategy.

Definitions:
t The current week
$CS(t)$ Number of charging stations that can be built in week t based on exponential growth function
$p_i^{\mathrm{succ}}(\mathrm{t})$ The percentage of successful charging attempts in region i during week t
$\mathrm{new}_i(t)$ The number of stations to be built in region i in week t

sort all regions i into stack L according to $p_i^{\mathrm{succ}}(\mathrm{t})$
var *avail* $= CS(t)$
while *(avail* > 0*)* **do**
  `// Region with lowest success probability is on top of stack`
  $i =$ **pop** L
  $\mathrm{new}_i(t) = 2^{\mathrm{new}_i(t-1)}$
  Build `min`(*avail*,$\mathrm{new}_i(t)$) charging stations in region i
  avail $=$ *avail* $-$ $\mathrm{new}_i(t)$
end

This probability can be computed for every time window and for each region by only considering the respective charging events.

From an economic perspective, the load of a charging station might be the decisive factor for profitable operation. Let $CE(t)$ be the charging events in a given time interval t and $\#CS(t)$ the overall number of charging stations (each with 2 outlets) in this interval, then the overall system load can be computed as:

$$Load(t) = \frac{\sum_{e \in CE(t)} \text{duration of } e}{\text{total time} \cdot \#CS(t) \cdot 2} \tag{6}$$

Again, statistics for single regions or single charging stations can be computed by only considering the respective subset of $CE(t)$.

Table 1: Excerpt of an event list of charging events for a certain region (sorted in chronological order regarding starting times).

ID	Start [hh:mm]	Duration in [hh:mm]	Char. Station	Outlet	Status
1	14:35	01:25	1	1	successf.
2	14:55	00:23	3	2	successf.
3	15:23	00:59	7	1	successf.
4	15:33	04:20	6	1	successf.
5	15:39	02:35	5	2	successf.
6	15:55	01:15	1	2	successf.
7	16:03	01:08	16	2	successf.
8	16:11	03:25	2	1	successf.
9	16:25	00:28	1	1	successf.
10	16:34	00:33	6	2	successf.
11	16:39	02:11	1	1	failed
12	16:47	00:48	2	2	successf.
13	17:08	00:59	4	1	successf.
14	17:11	14:15	2	1	failed
15	17:27	04:25	3	2	successf.

Load and success probability give an indication of how well the charging infrastructure operates. As a last output measure, we propose the theoretical waiting time, that is, the duration a driver would have to wait until one outlet of the charging station becomes available. For this, we assume that each vehicle will queue in front of the charging station, regardless of queue length, time of day, and charging duration of vehicles in front. This output measure is purely theoretical, however, it will react more sensitively to a mismatch between supply and demand as waiting times will quickly grow. The average theoretical waiting time $\phi wait(t)$ is simply the waiting time of all individual charging events normalized by the number of charging stations $\#CS(t)$ (each with 2 outlets) for a given time interval t.

$$\phi wait(t) = \frac{\sum_{e \in CE(t)} \text{wait time of } e}{\#CS(t) \cdot 2} \tag{7}$$

5. RESULTS

In this section we present example simulation results as a demonstration of the capabilities of our simulation model. We simulated the federal state of Bavaria from 2016-01-01 to 2020-12-31.

We analyzed three different expansion scenarios: The first one is a scenario where no new publicly accessible charging stations are built (denoted as *No Expansion*). This serves as a benchmark in order to understand the effect of a growing number of EVs on today's charging infrastructure. We additionally simulated the *Success* and *Target* expansion strategies (see Section 4.2). The threshold τ for *Success* was set to 0.95. For the *Target* strategy, we assume a target number of 7,000 charging stations for the entire federal state.

Due to the variety of regions (71 administrative districts and 25 independent cities) it is not possible to show results for every single municipality. As an example, we choose a small independent city in Bavaria and present different results including the number of daily charging events, percentage of successful charging events, the mean load of charging station, the theoretical waiting time, and finally the expansion of charging stations until the end of 2020.

Figure 6 shows the number of daily charging events for the entire simulation period. As expected, an exponentially increasing number of EVs leads to an exponentially growing number of charging events (cf. Equation 3). The variations originate from the applied Gaussian noise.

In Figure 7 the percentage of successful charging events according to Equation 5 is depicted. In the *No Expansion* scenario it can be observed that the percentage of successful charging events declines from 95 % in 2016 to approximately 55 %. Hence, this scenario is useful to see the consequences when no new charging stations are built.

The *Success* strategy (blue line) was able to successfully ensure a 95 % success rate, showing only minor fluctuations around the fixed threshold τ throughout the entire observation period. For the *Target* expansion strategy (red line), the success rate drops under 90 % between the years 2017 and 2018. This is a direct effect from the competition of the city with other regions within Bavaria regarding the allocation of charging infrastructure. In this period there were other regions with a lower percentage of successful charging events, receiving priority for newly built charging stations. These are mainly regions that already today do not have a sufficient number of charging stations. Once enough charg-

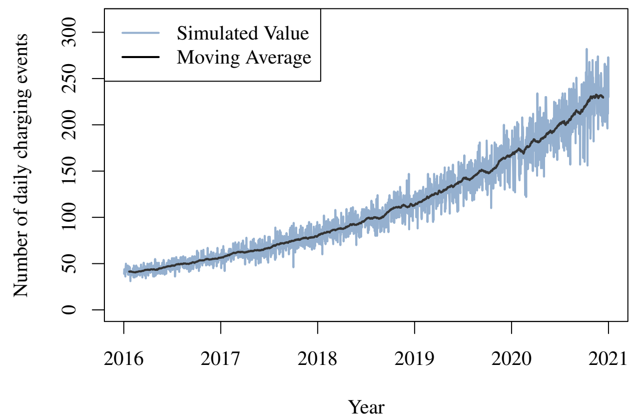


Figure 6: Number of daily charging events until 2020 for a small independent city in Bavaria.

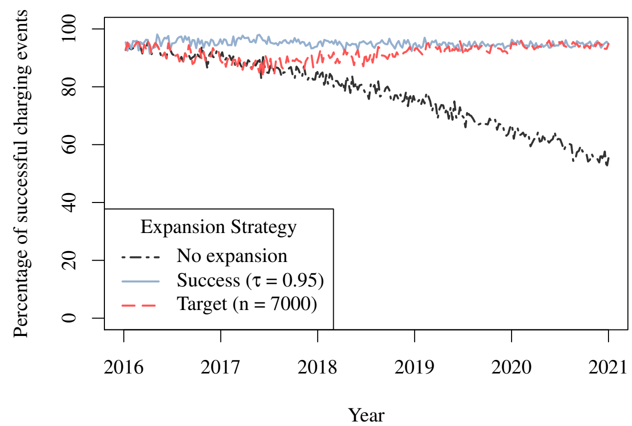


Figure 7: Percentage of successful charging events from 2016 to 2021 for a small independent city in Bavaria.

ing stations are deployed in these regions (after 2018), the success percentage for the presented city approximates 95 %.

Investigating the mean load of charging stations (Figure 8), we observe that the high success probabilities achieved using the *Success* and *Target* strategies come at the price of mostly idle charging stations. In both scenarios (red and blue lines), the average load of charging stations did not exceed 20 %, arriving at values as low as 10 % at the end of 2020. Even without building new infrastructure (black line), the load did not exceed 40 %. This is caused by low demand after work until the next day, further affected by standard trading hours in Bavaria (06:00 - 20:00) (cf. Figure 4a). From an operator perspective, it might be more logical to achieve a higher average load rather than high success rates. Our model design also allows to define expansion strategies with regard to the mean load of charging stations to arrive at a more economical expansion plan.

The average theoretical waiting time is depicted in Figure 9. Without building new charging stations, the theoretic waiting time grows exponentially. For instance, in the end of 2020 the theoretical waiting time amounts to over 50.000 minutes per charging attempt, which is more than 34

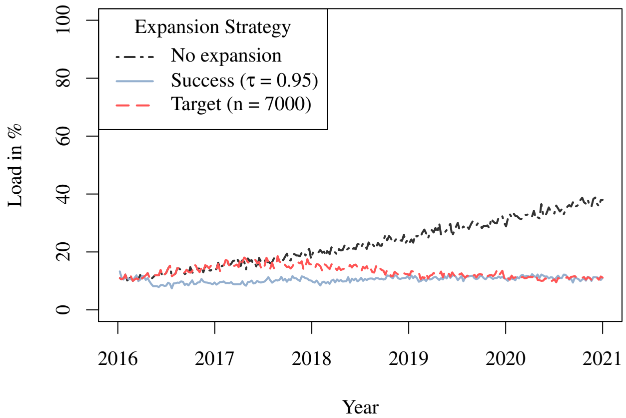


Figure 8: Mean load of charging stations from 2016 to 2021 for a small independent city in Bavaria.

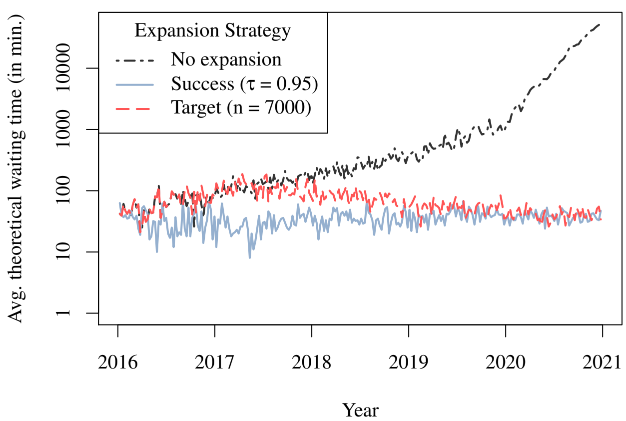


Figure 9: Average theoretical waiting time from 2016 to 2021 for a small independent city in Bavaria (y axis is in log scale).

days. Consequently, a significant mismatch between supply and demand is identified. The *Success* strategy contributes to keep the theoretical waiting time on a constant level of approximately 40 minutes. In the *Target* strategy, the theoretical waiting time increases to approximately two hours until mid 2017. After that, we observe an average theoretical waiting time of approx. 40 minutes.

The core output of our simulation is the spatial and temporal charging infrastructure plan, i.e. for a certain region we obtain a temporal expansion plan for building charging stations. Figure 10 shows the expansion of charging stations in a weekly resolution. For both the *Success* and *Target* scenarios, we observe that the building of only one charging station per week is not sufficient to catch up with the growing demand of electric vehicles. At some times, it was necessary to build the double, fourfold, or eightfold etc. number of charging stations in the subsequent week (cf. blue line at 2018 or red line at 2020 in Figure 10). Both strategies coincidentally arrive at a similar number of charging stations by the end of 2020, however, the building schedule strongly differs. Please note, that different values for τ would lead

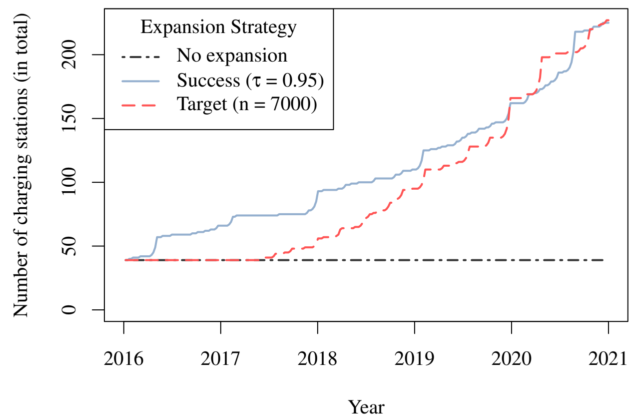


Figure 10: Temporal construction of charging stations from 2016 to 2021 for a small independent city in Bavaria.

to a different number of charging stations. The centralized *Target* strategy prioritized other under-supplied regions, delaying the beginning of building new stations until mid 2017. This delay leads to a steeper increase compared to the *Success* strategy where charging stations are added right from the beginning.

6. DISCUSSION

The presented simulation model is mostly of empirical nature and intended to assist stakeholders and policy makers in planning the building of charging infrastructure. The most challenging part for such a model is validation. Unfortunately, the data needed for validation is not yet available as electromobility and statistical data collection of charging stations is a rather new domain. Therefore we did not attempt to model charging behavior of individual vehicles, but assume that the utilization of today's charging stations is a direct result from a complex set of parameters that, without large amounts of data, it is not possible to model. By sticking closely to the distributions of the empirical input data, we abstract away from these parameters.

To achieve at least some level of validation, all models and results were discussed with domain experts. According to these experts the current differences in the utilization of charging stations located in independent cities and administrative districts are represented adequately by the provided empirical data.

The sparseness of data also required us to make various assumptions (see Section 3). The way the input data is used, however, allows the simulation to scale with the data quality of the input. The more information about charging stations and charging events is available, the more accurate we assume the predictions will become. We therefore recommend to iteratively use this modeling approach as soon as higher quality input data is available.

7. CONCLUSIONS

EVs contribute to more sustainable future transportation systems. In order to meet the announced EV targets, a significant number of publicly accessible charging stations is required. Therefore, many countries worldwide define expansion targets for charging stations. However, determining when and where new charging stations should be built is a challenging task.

In this paper we addressed this issue and developed a spatial and temporal charging infrastructure planning tool using discrete event simulation. Based on comprehensive analysis of empirical data about the utilization of charging stations, we derived models for the starting time and duration of charging events. Our simulation model allows to evaluate different expansion strategies with regard to various output metrics such as the likelihood of charging attempts to be successful, the average load of charging stations, and the theoretical waiting time, a measure that quickly reacts to a mismatch between supply and demand. As a proof of concept, we demonstrate the capabilities of our model for a city in the German federal state of Bavaria, where it is already used to assist stakeholders and policy makers.

Future work includes the investigation of different scenarios and an iterative application of the presented modeling approach. As more and more charging stations become equipped with a back-end connection, the picture that can be drawn from the collected data becomes more complete. This data could also be used to evaluate how the share of electric vehicles and the utilization of charging infrastructure will develop over time. This would allows us to derive specific scenarios for different regions to develop more accurate models for the observed charging behavior. The data could also be used for backtesting to validate the proposed approach.

8. ACKNOWLEDGMENTS

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