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How to Distribute Charging Requests of Electronic Vehicles? A Reservation-based Approach

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Abstract

The number of electronic vehicles increase steadily while the space for extending the charging infrastructure is limited. In particular in urban areas, where parking spaces in attractive areas are famous, opportunities to setup new charging stations is very limited. This leads to an overload of some very attractive charging stations and an underutilization of less attractive ones. Against this background, the paper at hand presents the design of an e-vehicle reservation system that aims at distributing the utilization of the charging infrastructure, particularly in urban areas. By applying a design science approach, the requirements for a reservation-based utilization approach are elicited and a model for a suitable distribution approach and its instantiation are developed. The artefact is evaluated by simulating the distribution effects based on data of real charging station utilizations.

Keywords Electronic vehicle · Reservation system · Utilization improvement · Charging station · Parking · Simulation

1 Introduction

The relevance of electronic vehicles (EVs) and its proportion of all car registrations increases steadily. In the months of January to March 2022, registrations of EVs in Germany were increased by 29.3% compared to the previous year [16]. However, several challenges that hinder the large-scale adoption of EVs exist. On the one hand, the range of EVs is too short, so that long-distance trips need to be well planned in advance [6, 20, 35]. On the other hand, charging an EV takes much longer than refueling an internal combustion engine, which affects the availability of e-charging stations [6, 35]. Particularly, highly frequented charging stations in city centers are often already occupied upon arrival. This leads to charging traffic, an unwanted search for free charging stations, and frustration. Against this background, reserving an EV charging station in advance would save time for EV drivers and the charging station operator may use reservations to better distribute and extend the utilization of its charging stations.

In previous research, utilization improvement is usually carried out with the help of systems that process real-time information. These systems partially use information regarding the current traffic situation or the charging status of all EVs in the closer environment in order to plan an optimal charging strategy [14, 19]. These reservation approaches have in common that they expect a very well equipped communication infrastructure, in which all EVs may communicate with each other and with all charging station operators in the EV's environment. Such an infrastructure is not broadly available yet and its setup may take years or even decades. In Addition, data privacy concerns need to be handled [21]. Thus, a solution for distributing the overall charging station utilization that works without a full information transparency is needed.

Against this background, the paper at hand aims at designing a reservation system for EV charging stations that enables distributing the station utilization without requiring a full information transparency. This research goal is achieved by applying a design science research approach [13, 28] combined with interviews [18] and simulations [37]. For the latter, we got access to the utilizations of 49 EV charging stations in a large city in Germany between 2020 and 2021.

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The paper contributes to the body of knowledge in three ways. First, requirements for an EV charging station reservation system as well as parameters for a utilization distribution approach are presented. Second, we provide a model for a reservation distribution approach and its instantiation through a mobile app. We conducted five iterations and refined the model according to the simulation results and challenges we were confronted with during the development cycle. Third, we provide insights into the applicability of the developed reservation system by simulating its effects on the utilization distribution.

The structure of the paper is as follows. The related work of reservation and utilization improvement of EV charging stations is outlined in Section 2. Additionally, we workout the research gap, which motivates the current research work. Section 3 comprises the methodology, which follows the design science research paradigm. Section 4 contains all iterations to receive the finished artifact. Section 5 discusses the results and points to future research.

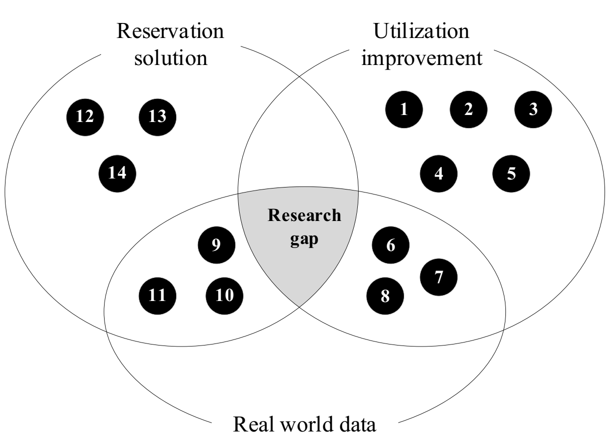
2 Related Work

The management of and search for parking lots is not new and was researched since 1998 [32]. Modern approaches comprise hierarchical approaches to find parking spaces [15] or approaches to consider map views to simplify the search for free parking spaces [8]. Therefore, Eckhoff et al. (2017) use historical occupancy data to display a prognosis of the number of available parking spaces. Next to the search for free parking slots, several research works investigate the utilization of parking spaces. For example, Pengzi, et al. [29] analyze five different parking areas with different capacities in order to develop a neural net for predicting the parking space utilization. Nowadays, so called smart parking systems are discussed [10]. These systems may receive parking space requests from all drivers within the closer environment and reserve a matching parking space. Geng and Cassandras [10] also mention the challenge to guarantee the availability of a reserved parking space and suggest solutions such as the installation of wirelessly controlled barriers. Missing guarantees in parking reservation systems is a challenge that is often discussed in literature [25, 30]. EV charging stations are also confronted with that problem.

The article at hand primarily investigates the reservation and utilization improvement of EV charging stations. In addition to traditional parking management solutions, several research works exists that particularly care about EV charging stations. We categorize these works with a focus on *reservation solution*, *utilization improvement,* and whether they applied *real world data* for evaluation. Figure 1 summarizes the results and points to the research gap (grey area), which we address in this paper.

2.1 Reservation Solution

Cao, et al. [5] apply block chain technology to connect the EV charging stations and to process user reservation requests. The approach is based on a user score calculated by the user's behavior based on two rules: punctuality of the car arrival at the right charging station and keeping the reserved amount of energy. If the EV driver does not keep the rule, the approach penalizes the driver by price changes. The system was tested with real world data from Manhattan, USA. A similar penalty system is also used by Liu, et al. [21], who are primarily concerned with the issue of user privacy and the security of the reservation system. They use a penalty system for customers who reserve a charging station but do not use it. Furthermore, the impact of reservations on users' travel time and waiting time was studied [2, 3]. The authors



1: Vaidya and Mouftah [33]
2: Li, et al. [19]
3: Zou, et al. [38]
4: Atallah, et al. [1]
5: Cao, et al. [4]
6: Ji, et al. [14]
7: Zarkeshev and Csiszár [36]
8: Ding, et al. [7]
9: Basmadjian, et al. [2]
10: Basmadjian, et al. [3]
11: Cao, et al. [5]
12: Liu, et al. [21]
13: Fotouhi, et al. [9]
14: Orcioni and Conti [26]

Fig. 1 Existing reservation and utilization solutions divided reservation types into "Ad-Hoc" and "Scheduled". Their simulations were conducted based on real locations of charging stations in Germany and the Netherlands. The results show time savings when using pre-scheduled reservations and longer travel times and waiting times when using ad-hoc reservations. Zarkeshev and Csiszár [36] propose a system, which is based on the communication between the charging station and the EV. The EV makes a reservation proposal on its own, which the user can confirm or reject. Orcioni and Conti [26] propose extensions to the Open Charge Point Protocol (OCPP) to allow reservations with fixed start and end times.

2.2 Utilization Improvement

Research investigated the problem of over or underutilization of charging stations from two perspectives. Either the waiting time at charging stations should be reduced or the whole network utilization and its improvement is focused. Fotouhi, et al. [9] designed a stochastic model that describes the charging behavior of different EV drivers. The parameters of the model can be adjusted to represent arbitrary environments. This model can be used to predict the required power capacities and congestion at charging stations. Other authors propose centralized systems that manage the charging of multiple EVs [1, 4, 7, 14, 19, 33]. These approaches have in common that they expect tremendous information about all EVs and charging stations in the environment and some also integrate public transportation systems [14, 19]. The goal of these systems is to reduce the waiting time at the charging stations. Li, et al. [19] propose a charging navigation strategy that uses price incentives to encourage users to approach specific charging stations. They tested their strategy using simulations and worked out that congestion at central charging stations can be reduced and that the utilization rate of decentralized charging stations can be increased. Ding et al. [7] developed a mechanism to compensate charging station operators and EVs that are disadvantaged by the optimized distribution.

On the other hand, Cao, et al. [4] describe a system that can minimize the waiting time for EVs at charging stations. For this, the EVs are divided into "High Prioritized-EV" and "Low Prioritized-EV". The EV sends a charging request to the system, which then searches for a suitable station. This system was tested using simulations based on the geographical data and traffic of the city of Helsinki. A centralized management system is also proposed by Atallah, et al. [1]. In this system, multiple charging requests are processed simultaneously to design the best possible charging strategy for all stakeholders aiming at reducing the waiting time. Ji, et al. [14] developed personalized charging strategies using an intelligent transportation system based on time, distance, and cost. Their simulations were performed on abstracted data from the city of Chengdu, China. The results show a reduction in average charging cost and waiting time. Zou, et al. [38] propose a coordinated charging distribution based on a “progressive second price” auction mechanism. Vaidya and Mouftah [33] present a system that enables effective slot allocation. The user sends a charging request to the system. The system then calculates the optimal solutions based on all available charging stations.

2.3 Real World Data

In order to verify the usefulness and applicability of EV charging station reservation approaches, simulations or case studies are usually applied. Some authors access real-world data to perform the analyses as close as possible to reality [2, 3, 5, 7, 9, 14]. Out of them, some additionally use the real locations of charging stations [2, 3, 9]. Cao, et al. [5] use the number of EVs in a given area and Ding, et al. [7] observed the charging behavior of EV drivers to keep their simulations as realistic as possible.

Both the reservation and the utilization improvement of EV charging stations have already been considered and investigated from different perspectives. However, these reservation methods do not address the issue of improving the utilization of charging stations. Research in the field of charging station utilization does not use reservations for utilization optimization. Rather they focus on managing utilization centrally, which requires that all the information needed to process the charging requests of EVs and to plan the optimal sequence of charging processes is available, which is unrealistic from today's perspective. The improvement of charging station utilization by using a reservation system remains an open topic, which motivates the paper at hand.

3 Research Design

The research design follows the design science research (DSR) approach [28]. Design Science has its origins in engineering and the "Sciences of the Artificial" [31] and is essentially a problem-solving paradigm. Design Science creates and evaluates IT artifacts that are intended to solve organizational problems [13]. These IT artifacts can take the form of constructs, models, methods, and instantiations [13, 22]. There are a variety of models by which DSR can be applied [12, 17, 22, 27]. Of these, the process model of Peffers, et al. [28] is the most frequently cited [34]. In the process model, six phases are passed through in an iterative process. We provide theses phases and its adaptation to the research goal at hand in Fig. 2. In the following, we outline each process phase and explain its adaptation to the research problem at hand.

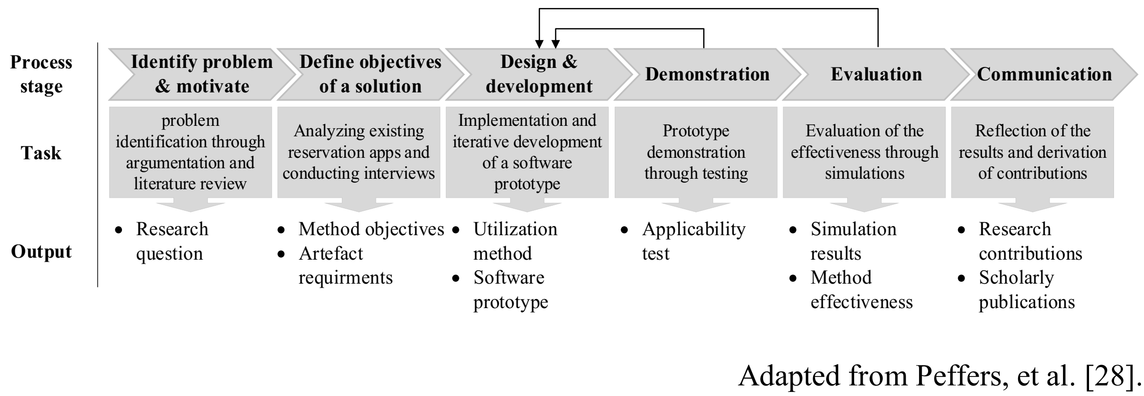


Fig. 2 Research design, Adapted from Peffers, et al. [28]

To *identify the problem* and to *motivate* our research work, we received insights into a large German EV charging station operator, who described the problem as follows. In the near feature, much more EVs will have the need to charge while the charging infrastructure (power supply and space) in urban areas is limited. Particularly EV charging stations, which are close to hot spots and famous places, will most likely be occupied most of the time, while other charging stations will remain available. Even before the completion of the EV revolution, this trend is already observable when analyzing the operator's utilization data of the charging stations. Next to that, information transparency between the charging station operator and all EVs in the environment is not given yet. Moreover, it is questionable whether this information transparency will be available in the future because of data privacy concerns of the drivers. Against this background, we conducted a literature review for EV charging station reservation systems as well as for strategies to improve the station utilization (see Section 2). So far, no scholarly work investigates the combination of a reservation system and a utilization improvement. Furthermore, current approaches require a full information transparency, which is – at least at the moment – unrealistic.

In the following process step, we *define the objectives of the solution* by analyzing existing reservation apps and conducting interviews with EV drivers and the charging station operating company. For this purpose, apps that display charging stations and reservation apps were examined and requirements for the app prototype were derived. Based on the requirements analysis, an initial mock-up was created by using the online tool figma.com. The mock-up represents the initial reservation approach and acts as input for the interviews.

The criterion for selecting interview partners comprises the need to drive an EV privately or as a company car. The charging station operator supported the contacting of the interview partners. In total, six interviews were conducted using Microsoft Teams. The interviews were conducted between December 7 and December 22, 2021. The duration per interview averaged 18 min, with the shortest interview lasting 14 min and the longest lasting 23 min. Table 1 provides an overview of the demographics of the interview participants. In addition to the six EV drivers, we also had the opportunity to interview the innovation manager of the EV charging station provider.

The interviews were transcribed using the transcription service Amazon Transcribe. Subsequently, any errors resulting from the automatic transcription were corrected by hand. For analyzing the interviews, we applied a qualitative content analysis approach [23, 24] and follow a inductive category development procedure.

The interview results lead to concrete objectives of the reservation solution, which are the basis for the *design and development* stage. Two artifacts with two contribution types [11] are provided in this research phase: a *method* for the improvement of EV charging station utilization (Level 2) and an *instantiation* of that model in a software prototype (Level 1). Since we apply an iterative procedure, the method as well as the software prototype changes and improves from iteration to iteration. In total, we conducted five iterations to develop a suitable utilization improvement method and one

Table 1 EV driver demographics

ID	Gender	Age	EV drive experience	Ownership
A	male	50–55	12 years	Private and company car
B	male	35–40	3,5 years	Private and company car
C	male	30–35	2,5 years	Company car
D	male	30–35	0,5 years	Private car
E	male	55–60	1 year	Private car
F	male	30–35	2,5 years	Private car
G	male	55–60	9 years	Company car

further iteration to implement the approach into a mobile app-based reservation system.

The *demonstration* phase aims at testing the applicability of the iteratively developed method and its instantiation. Thereby, we test whether the utilization improvement method is working in the app prototype. However, within the demonstration phase, we do not evaluate the effectiveness and efficacy of the method, which means that at this point we solely know that the app is working with the iteratively improved utilization method.

Estimating the effect of using the reservation system and confirming its applicability is the objective of the *evaluation* phase. In order to evaluate the effects of the reservation approach and to determine the best possible values for the parameters, we conducted simulations [37] with data from a German EV charging station operator. For the simulations, the charging processes at 49 charging stations in a large German City from the years 2020 and 2021 are used. Each dataset has the following attributes: station ID, address, charging day and charging time. In each simulation, we vary the station of each charging request, which the driver may have reserved by applying the reservation system. The distance of each charging station to the city center are listed in Table 2.

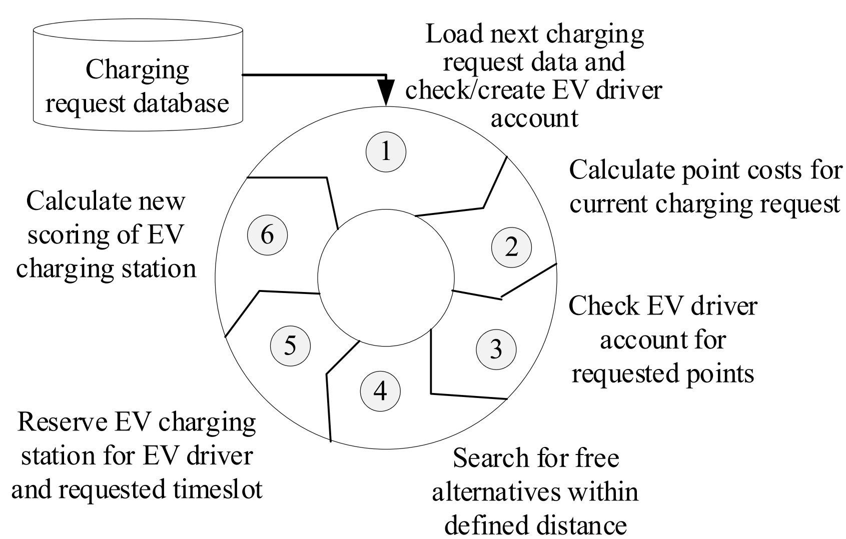
In each simulation, we iterate through all charging requests and calculate a new distribution based on the set parameters. Figure 3 depicts the simulation process, which contains six abstract steps. The first step comprises the setup of an virtual EV driver account, which can store the current reservation points of an EV driver. In case of an existing EV driver account, the account is selected for the next operation, which is to calculate the requested points for reserving the EV charging station, which may change depending on the reservation behavior and time (step 2). In step 3 the algorithm checks, whether the EV driver has enough points for the requested EV charging station. If he has enough points for the reservation the algorithm directly conducts step 5 and reserves the EV charging station. If the EV driver has not enough points, the algorithm conducts step 4 and selects an alternative charging station, which is able to reserve depending on the remaining

Table 2 Station distance to city center

sid	d	sid	d	sid	d	sid	d	sid	d
0	6,356	10	525	20	128	30	5,601	40	1,625
1	2,440	11	384	21	818	31	3,700	41	1,533
2	538	12	1,987	22	909	32	3,123	42	4,312
3	2,841	13	1,028	23	3682	33	5,907	43	1,454
4	3,341	14	3,019	24	8,889	34	2,814	44	4,994
5	2,029	15	1,618	25	387	35	5,181	45	4,743
6	1,499	16	2,862	26	940	36	1,520	46	5,660
7	1,291	17	2,399	27	519	37	1,545	47	2,266
8	213	18	113	28	1,467	38	1,689	48	925
9	1,779	19	3,050	29	1,423	39	1,625		

sid station ID, *d* distance to city center in meter

Fig. 3 Simulation process



reservation points. The basic assumption for the alternative selection is that am EV driver will most likely choose another EV charging station based on the distance to the initially selected one. The final step comprises the recalculation of reservation costs of the station of the current charging request. The simulation stops when all charging requests from the database are processed.

The utilization data of 2020 is used to calculate the initial utilization types of the EV stations. The charging processes of the year 2021 are applied to calculate various simulation scenarios in order to improve the distribution results. The basic assumption for all simulations is that the EV drivers use the reservation system for each charging process. The start and end time as well as the plug type of the charging process is not changed, which means that charging processes may expire if no suitable charging station can be found. In 2020, 28,393 charging operations were performed at the 49 charging stations, and in 2021, 40,818 charging operations were performed. The average utilization rate across all charging stations is about 12.88%. The 40,818 charging operations in 2021 were performed by a total of 5022 different users. However, 1311 of them performed only one charging process at the charging stations. These EV drivers are very dependent on the parameter "Start points", since the users have no possibility to earn points by repeated charging processes. Each simulation and its parameters acts as one iteration and lead to the change of the utilization method and consequently a change of the app prototype.

To evaluate the effectiveness of the algorithm and its parameterization, we calculate the daily utilization of each EV charging station as follows:

$$A_c = \frac{\sum_{h=0}^{23} \frac{Vc(h)}{Lpc}}{24} \tag{1}$$

To calculate the utilization of charging stations on a certain weekday (Monday to Sunday), we applied the following formula:

$$A_{cd}(weekday) = \frac{\sum_{d=1}^{S_{ow}} \sum_{h=0}^{23} \frac{Vc\_weekday(d,h)}{Lpc}}{S_{ow} * 24} \tag{2}$$

In order to consider rush hours and less demanded time frames, we calculate the utilization for each time frame. Time frame one ranges from 0:00 am to 7:59 am (cd1), time frame two ranges from 8:00 am until 6:59 pm (cd2) and time frame three ranges from 7:00 pm until 11:59 pm (cd3):

$$A_{cd1}(weekday) = \frac{\sum_{d=1}^{S_{ow}} \sum_{h=0}^{7} \frac{Vc\_weekday(d,h)}{Lpc}}{S_{ow} * 8} \tag{3}$$

$$A_{cd2}(weekday) = \frac{\sum_{d=1}^{S_{ow}} \sum_{h=8}^{18} \frac{Vc\_weekday(d,h)}{Lpc}}{S_{ow} * 11} \tag{4}$$

$$A_{cd3}(weekday) = \frac{\sum_{d=1}^{S_{ow}} \sum_{h=19}^{23} \frac{Vc\_weekday(d,h)}{Lpc}}{S_{ow} * 5} \tag{5}$$

Variables:

A_c	utilization of charging station c (c $\in C$)
C	set with all operated charging stations
Y	all days within a year
h	hour [0..23]
d	day (d $\in Y$)
S_{ow}	Station operating weeks (some stations were not operating each week)
V_c	function that returns the number of charging activities of charging station c in hour h
Vc_weekday(d,h)	function that returns the number of charging activities of charging station c on weekday d in hour h
Lpc	Number of charging plugs of charging station c

Finally, we created a first draft for a method and its instantiation that is able to address the upcoming problem of limited EV charging stations and the expected unequal distribution of EV charging processes. The *communication* of the research contributions takes place through the paper at hand.

4 Designing a Reservation System for EV Charging Stations

4.1 Objectives of the Solution

In order to determine the general requirements for an app with a reservation function, we analyzed existing apps and websites for both e-mobility and reservations. For reservation requirements, we analyzed the websites of booking.com and check24.de, which are travel systems and offer a very mature reservation functionality. For special e-mobility requirements, we analyzed ladenetz.de and the Enbw mobility + app. Both platforms enable the search for EV charging stations. In addition to the analysis of related platforms, we interviewed seven EV drivers and asked for their requirements and criteria to select an EV charging station. In total, we derived seven functional requirements, which are summarized in Table 3. The derived functions are the basis for the method development and instantiation.

At the beginning of the research project, we get the opportunity to interview the innovation manager of an EV charging station operator. He elaborates about the utilization of its charging stations when the number of EVs continues to increase and the capacities of attractive stations cannot fulfill the charging requests of EV drivers anymore. His basic requirement is an *equally distributed utilization*, so that even more attractive charging stations remain available for ad hoc EV drivers. When asking the EV drivers about their attitude towards using a *reservation* system, six out of seven respondents said they would like to use it: "if I knew I was going to Holland to the seaside now, I might reserve it in advance" (Respondent C). Solely one respondent felt that this option is less interesting and states, "all flexibility is lost then" (Interviewee E).

We also asked the interviewees about their willingness to choose a less popular charging station if they would be compensated. For this purpose, we discussed reduced reservation costs and a discount system. However, the response to these proposals was predominantly negative. Four out of seven respondents stated that they would not drive to another charging station for a reduction in reservation costs. Respondent G says, "not only for lower costs". Regarding the discount system, five respondents said that such a system would be uninteresting for them because of the inconvenience of a detour: "If I had to accept a detour or longer walking distance for these discounts, I probably wouldn't use it." (Respondent F).

Both analyzed e-mobility platforms offer a *map view* that provides an overview about all charging stations in the closer environment. The *ability to filter* is important to select a relevant charging station. To do so, the plug type and parking slot size seems to be relevant information, which should be provided by the reservation system. Respondent F says, “I filter (if possible) by charging power and then by stations that are connected to the [customer’s operator] infrastructure”.

For the EV drivers it is important to receive detailed *charging station information*. Particularly, the plug types and the size of the parking slot are of interest. “What I am extremely missing in the whole charging infrastructure, are […] the descriptions of the places on site or also the filter possibility.” (Respondent B). By having a look in the Enbw e-mobility app, we also noticed that detailed information about the charging station is provided. Next, the reservation system needs to offer a *time slot determination*. Surely, each reservation system must also enable to determine a reservation time. Next to the analyzed platforms, the respondents also require for a precise time slot reservation function. “If I knew I had a time window of, I don't know, 15 20 30 min to be on site in that time window, and I'm guaranteed that the parking space is free to load, I would definitely want to pay money [for this service]” (Respondent B). Each reservation platform we analyzed offer a function to *cancel reservations*. Since the EV driver may ad hoc drive to a different destination, the reservation may be obsolete. In order to prevent penalties and free the reserved charging station, the reservation system should enable a cancelation.

Besides eliciting functional requirements, we also asked the respondents about their main criteria for selecting an EV charging station. The four main criteria were price, distance,

Table 3 Functional requirements

No	Requirement	Description / user story	Source
1	Equally distributed utilization	As an EV charging station operator, I would like to get equally distributed utilizations of my EV charging stations	EV charging station operator
2	Reservation	As an EV driver, I would like to reserve an EV charging station	E-mobility apps, interviews
3	Map view	As EV driver, I would like to see all charging stations around my position in order to get a good overview	E-mobility apps
4	Ability to filter	As EV driver, I would like to set a filter for specific plug types in order to get a view on all relevant charging stations nearby	E-mobility apps, interviews
5	Providing charging station information	As EV driver, I would like to view additional information from charging stations so that I can get information such as the address, opening hours, plug types and price of the charging station	E-mobility apps, interviews
6	Time slot determination	As EV driver, I would like to determine the start and end time of the reservation	Reservation apps
7	Cancel reservation	As EV driver, I would like to cancel a reservation if I do not need it anymore	Reservation apps

availability and charging capacity of the charging station. After discussing the *price*, it turned out that the majority of interviewees do not perceive monetary aspects as effective, which is summarized by Respondent A: "Price doesn't matter at all; location is 100% more important". Three out of seven respondents even did not mention price as a criterion, which let us assume that the price is not a main criterion for the respondents for selecting an EV charging station.

With regard to *location*, on the other hand, six of the seven respondents stated that it played a major role for them when selecting an EV charging station. Respondent B says, "Proximity to the destination, that's clear. I don't really look at price at all". Respondent A puts it in that way: "Location is 100% more important". These results also explain the high occupancy rates of some few attractive EV charging stations, while more unattractive stations remain unoccupied most of the time even when they are not far away.

Six respondents also mentioned the *availability* of the charging station as an influencing factor. Respondent A stated that "when I drive into town, I always look to see if there is one free". This is particularly interesting because a reservation function guarantees the availability of the charging station for the EV driver. Furthermore, three of the respondents mentioned that they have noticed an increase in occupied charging stations over the last few years, which additionally motivates the need for the introduction of a reservation function.

Three respondents mentioned the *charging capacity* of the charging station as a criterion. Respondent E perceives the charging capacity as his main criterion for selecting the charging station: "I select fast charging, so that is always the criterion, because I cannot and do not want to wait that long".

To sum it up, a reservation system must support the basic functions, such as time slot determination, map view, and cancelation. For an improved utilization of EV charging stations, the system should not work with monetary incentives because the location is mostly more important than paying more money. Surely, this requirement depends on the price of the station. However, having in mind that less wealthy EV drivers would be totally locked out from reserving an attractive EV charging station when the price exceeds a certain limit, motivates us to search for alternative ways of incentivizing.

4.2 Designing and Evaluating the Utilization Improvement Approach

4.2.1 Initial Setup

The interviews with EV drivers reveal a low interest in monetary incentives such as the reduction of reservation costs or the introduction of a discount system. The price of charging is perceived as rather ineffective. Against this background, we decided to setup a point-based utilization distribution method. The initial version of the reservation and utilization improvement method comprises five activities, whose sequence is depicted in Fig. 4.

At the beginning of each reservation process, the approach *calculates the point costs for the requested charging process* at a selected station. Has the EV driver enough points for reserving the EV charging station and the requested time slot, the approach checks whether the requested time slot is available. If this is the case, the approach *reserves the EV charging station for the EV driver* and depending of the Type of charging station it *calculates the new score.* If the EV driver has not enough points for the reservation or the requested time slot is not available, the approach searches *free alternatives within the defined distance.* Based on the distance to the originally requested EV charging station, the system choose the next best solution and *calculates the required points for the next alternative*. Has the EV driver enough points for reserving this charging station, the approach reserves it for the EV driver. If the EV driver has not enough points, the approach searches for other alternatives and again calculates its required points. If no alternatives are available, the charging process is omitted. In this case, the EV driver cannot reserve a station by using the reservation system. All configurable parameters of the distribution method are describes in Table 4.

We divided all EV charging stations operated by the EV station operator into three different types depending on its former utilization. Type-1 stations comprise EV charging stations that are rarely used and thus have a low utilization. Thus, Type-1 is the type of charging station that should experience an increased utilization through the implementation of a reservation system. Type-2 stations have a medium utilization, i.e. their utilization is in a good range and does not need a change. The Type-3 charging stations are attractive and have a high utilization rate relative to the other charging station types. They are the main object of investigation. The goal of the utilization improvement method is to decrease its utilization.

The reservation system is based on collecting and spending points for reserving EV charging stations. However, the points are not used for monetary discounts, but for the reservation itself. For each reservation, the EV driver needs points, which are calculated based on the charging station type and the reserved duration. A reservation is separated into 15-min slots. Reserving a charging station of Type-3 has the highest point costs per slot, while a reservation at a Type-1 charging station compensates the user and refunds points instead of deducting them. This system ensures that a user must reserve unattractive Type-1 charging stations in order to earn points. The EV driver may use these points to reserve Type-2 or Type-3 charging stations.

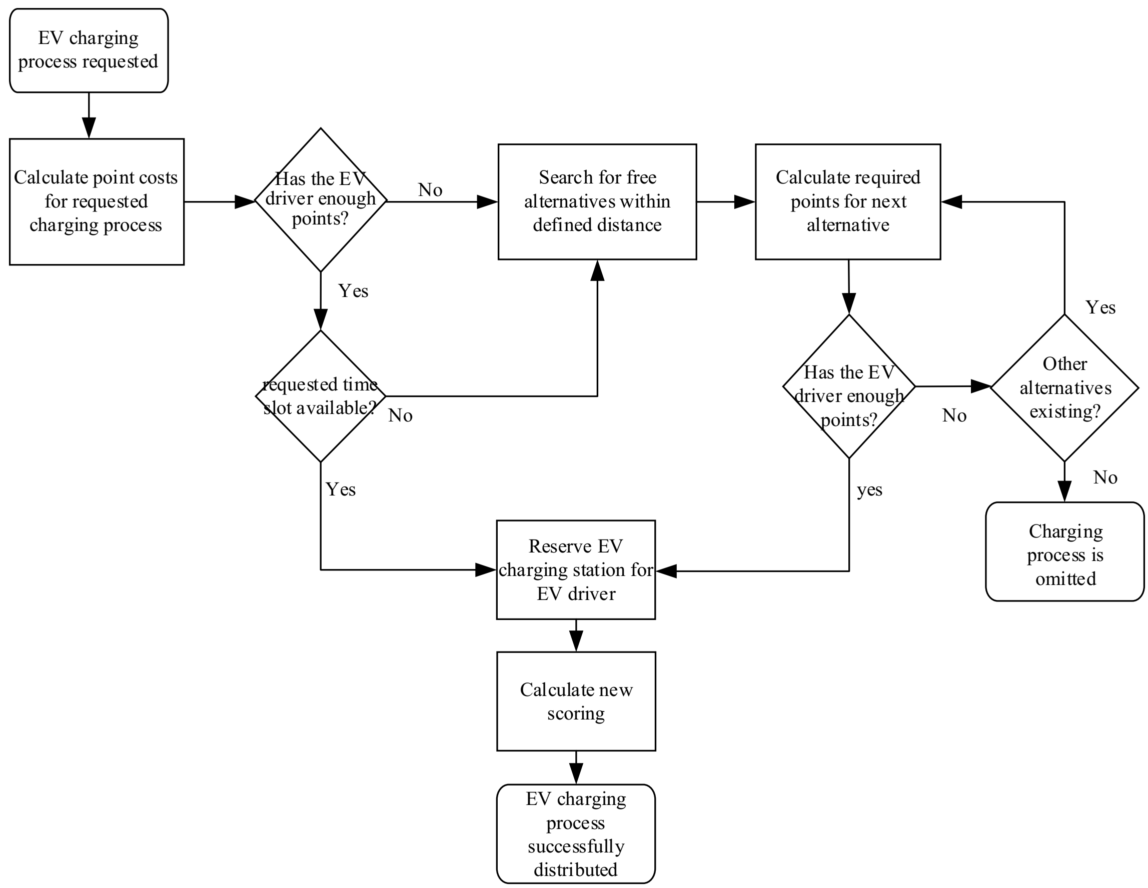


Fig. 4 Basic reservation and utilization improvement method

Table 4 Parameters for the utilization improvement algorithm

Parameter name	Description	Attribute type
Starting points	Determines the number of points a driver starts with	Numeric
Maximum points	Determines the maximum number of points a driver can receive	Numeric
Utilization type loading limit	Specifies the type of charging station regarding its utilization	Vector, containing categorical & numeric values
Utilization type point costs	Indicates the point costs per 15 min of reservation. Negative values indicate that the user receives points for reserving	Vector, containing categorical & numeric values
Alternatives distance	Specifies the maximum distance within which alternatives are searched for, starting from one EV charging station	Numeric

In the following, we present the artefact development iterations and its evaluations. The simulation data of each iteration as well as the initial state is provided in the table of Appendix Table 7.

4.2.2 Iteration 1: First Try

We calculate the utilization for each EV charging station at every hour of the day. We also care about the possibility of charging more than one EV at the same time because of multiple charging points at one station, so that no utilization of more than 100% can be achieved. The utilization of a charging station is always recalculated after the end of a day. Based on the utilization data from the years 2020 and 2021, the following values were taken as the first determination of the station type:

- Type-1 charging pole: A charging pole is determined as Type-1 if it has an average utilization of less than or equal to 10%.
- Type-2 charging pole: A charging pole is determined as Type-2 if it has an average utilization of more than 10% and less than or equal to 20%.
- Type-3 charging station: A charging station is determined as Type-3 if it has an average utilization of more than 20%.

All parameters for the algorithm in the first iteration are described in Table 5. It is important to notice that the allowed distances for alternative stations as well as starting and maximum points do not change within iteration 1 to 4 because we first focused on time and station type change effects.

Table 5 Parameter settings in iteration 1

Parameter name	Values
Starting points	50
Maximum points	100
Utilization type thresholds	Type-1: util. < = 10% Type-2: util. > 10% and < = 20% Type-3: util. > 20%
Utilization type point costs	Type-1: -1 point / time slot Type-2: 3 point / time slot Type-3: 5 point / time slot
Alternatives distance	No limitation (not set)

We demonstrate the applicability of the method by implementing it and evaluate the effectiveness by simulating the utilization distribution when the charging processes are limited by the reservation system. We compared the results of the applied approach with the actual utilization rates, which is provided in Fig. 5. After simulating the effects of the utilization distribution, we noticed a utilization decrease of the most attractive stations (e.g. station ID 18, 20, 25, 10, 9, 12, 17) and an occupancy increase of less attractive ones (e.g., 8, 27, 6). After applying the approach, 24 stations belong to Type-1 (initial 30), 20 stations belong to Type-2 (initial 8), and solely 5 stations belong to Type-3 stations (initial 11). The utilization rates are more flattened. However, we noticed a strong increase in occupying Type-2 charging stations. Furthermore, we observed a strong utilization difference between the different weekdays. There may still be overloads of a certain EV charging station on a certain weekday, which motivates the adaptation of the distribution method in iteration 2.

4.2.3 Iteration 2: Considering Weekdays

In order to address the weekday dependent utilizations of the EV charging stations, we changed the utilization distribution method in iteration 2 and considered the weekdays. As a result, an EV charging station receives seven different utilizations and can be of a different station type depending on the day of the week and its corresponding utilization. Figure 6 compares the simulated utilizations of the approach in iterations 1 and 2. At the end of the simulation period, the number of Type-1 charging stations increases (from 24 to 33), while both the number of Type-2 and Type-3 charging stations decreases (Type-2: from 20 to 15 and Type-3: from 5 to 1). In total, the utilizations are mostly lower than the utilizations in iteration 1.

After the change to individual weekdays, 1908 charging processes out of the 40,818 were skipped due to missing available stations, which can be afforded with the remaining

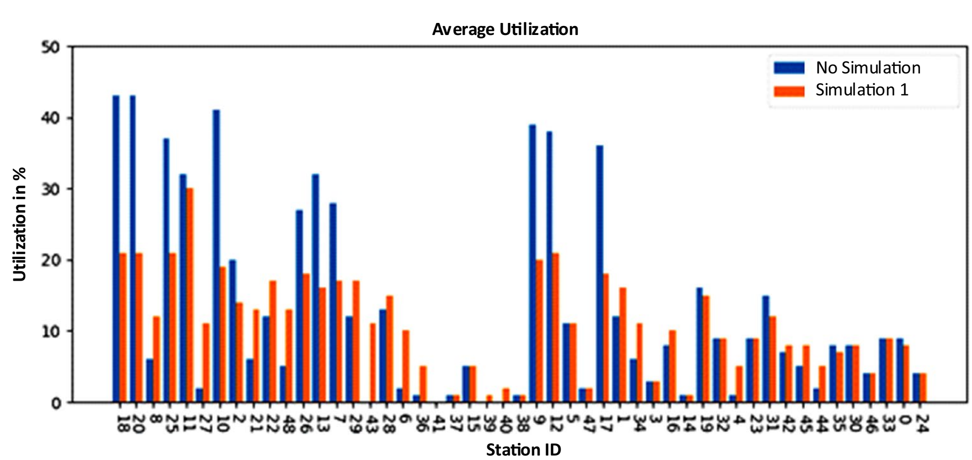


Fig. 5 Utilization distribution after iteration 1

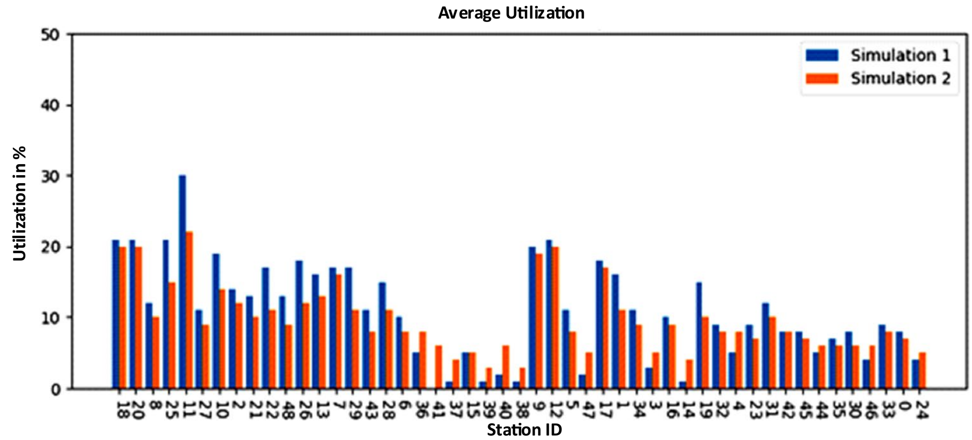


Fig. 6 Utilization distribution after iteration 2 (considering weekdays)

points of the EV driver. Certain days of the week experience more utilization, which means that the EV charging stations on these days belong to a higher type and require more points to reserve them. The supposed improved utilization can be explained by finding no matching alternatives for the user, as the remaining Type-1 charging stations are all fully booked. Since reserving the Type-2 or Type-3 charging stations for some charging processes is not possible due to the required points, they are omitted by the system, which is problematic because in real life the EV driver would most probably not use a reservation system, which does not allow reserving even a low attractive charging station. The low availability of Type-1 stations can be explained by the static determination of the utilization type thresholds (cp. Table 5). Stations remain in its type even when they are not or less utilized. This observation motivates a further improvement of the reservation approach, which leads to iteration 3.

4.2.4 Iteration 3: Station Type Flexibilization

In iteration 3, we solved the problem with fixed utilization thresholds and a static station type determination. For this purpose, the changed approach recalculates the thresholds after the end of a simulated day. The calculated values are then applied as new utilization thresholds for the current weekday and becomes effective in the following week. In order to get a flexible determination of charging station types, we list the utilization rates of all charging stations and sort them by their size in ascending order. We applied the 50% quantile for Type-1 stations and the 75% quantiles for Type-2 stations. All charging stations, which are above the 75% quantile, are determined as Type-3 stations. Figure 7 depicts the comparison between the results of iteration 2 and iteration 3.

By applying a flexible station type determination, no charging operations had to be omitted anymore. Accordingly, the utilization rate increases for many charging stations. However, due to constant changes in the utilization thresholds, it is no longer possible to reliably receive the number of charging stations per type. However, the highest utilization rate of an EV charging station is now 20% and the most frequent utilization is around 12%.

This utilization distribution is more flattened in comparison to our first try in iteration 1. However, we recognized that analogue to the different weekdays, the concrete time of the charging process influences the effectiveness of the system. In Table 6, we provide the average utilization rates

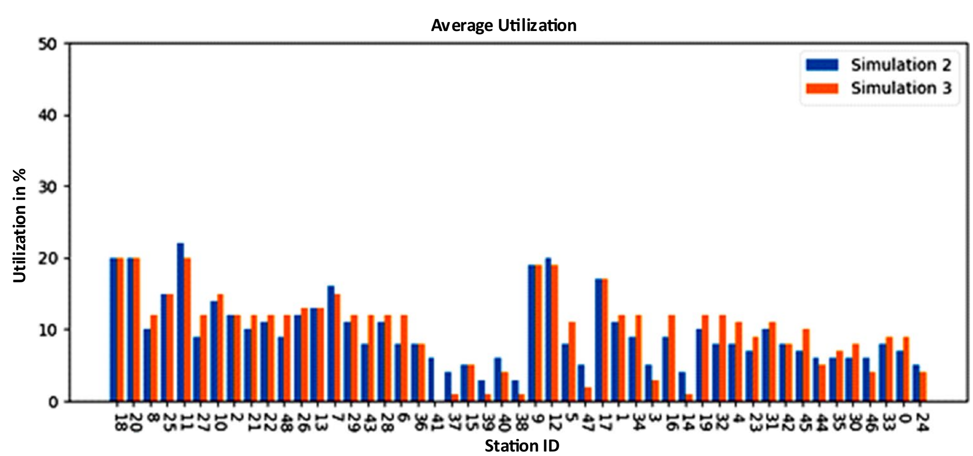


Fig. 7 Utilization after iteration 3 (flexible station types)

Table 6 Average utilization by timeframe

ID	Monday			Tuesday			Wednesday			Thursday			Friday			Saturday			Sunday		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Avg util	7.0	14.3	7.4	7.6	14.1	7.1	7.5	14.4	7.8	7.8	14.3	7.6	7.7	15.0	7.2	7.3	13.3	7.2	6.8	10.6	6.4

Timeframe T1: 0 am -7 am; T2: 8 am - 6 pm; T3: 7 pm - 11 pm

of all stations by weekday and time frame. Independently from the weekday, during the daytime, more stations are occupied than during the night. Against this background, we start a fourth iteration and consider day and night time.

4.2.5 Iteration 4: Considering Day and Night Time

Iteration 4 addresses the need to distinguish between day and night times. We decided to split the day into three timeframe: from 0-7am, 8am-6 pm and 7 pm—zero am. The calculation of the utilization thresholds remain by using the 50% and 75% quantiles as described in iteration 3. However, they are now separately calculated for each timeframe. This results in three different utilization thresholds per day and station. Figure 8 depicts the comparison of the utilization distribution between iteration 3 and iteration 4. We calculated the differences of the average utilizations as provided in Appendix Table 7 (simulation 3 and simulation 4). The mean utilization difference is 0.1% with a standard deviation of 0.01 (min -3.3%, max. 3.8%). Thus, the differences between simulation 3 and 4 are rather small, which indicates that implementing further time slots and thresholds for station type determination may not further improve the method. So far, we simulated the effect based on unchanged real-world data, which represent the EV charging processes in the year 2021. For such a low number of charging processes (~ 2 charging requests per day and station), the approach works well. However, having in mind that the number of EVs increases steadily, we need to test whether the method also works with more charging processes. In addition, the effect of the parameter distance and the change of the rewarded points need to be investigated, which motivates the fifth iteration.

4.2.6 Iteration 5: Changing Parameters and Increasing Charging Processes

In the previous iterations, we ignored the distance at which the alternative charging stations may be located. We limit the distance to 500 and 1000 m and again simulate the effects. The results reveal a weakness of the system. Because the charging stations are sometimes far apart, fewer alternatives are found by limiting the distance. This leads to a large number of charging processes being omitted. In the real world, this implicates that the EV drivers does not accept the detour. They solely have the option left to drive to the charging station without making a prior reservation and hope that it will be free when they arrive. Since the distance may be an optional filter parameter for alternative charging stations in the reservation app, it is uncritical for the approach. However, charging station operators should consider the risk of reservation losses due to distance constraints.

We also investigated the utilization impact of changing the point costs. We tested two more configurations:

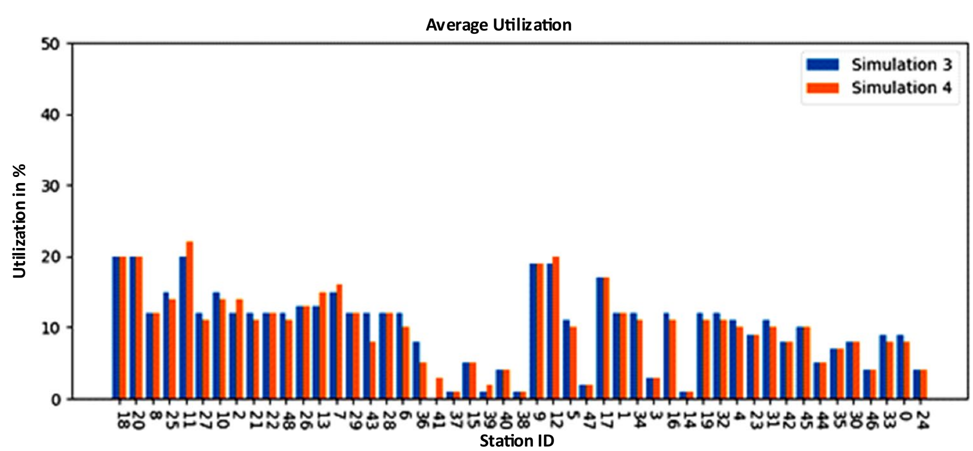


Fig. 8 Charging station utilization after iteration 4 (day & night time separation)

Type-1: -1, Type-2: 5; Type-3: 8 as well as Type-1: -1, Type-2: 1; Type-3: 2. An increase of point costs leads to a small utilization reduction at some few charging stations. We observed that the utilization is better distributed when applying higher point costs, but it is very likely that in a real environment users quickly lose interest in the system and consequently stop participating because they need to charge at unattractive Type-1 stations five times as long as they need for charging at a more attractive Type-2 station. Decreasing the point costs, on the other hand, leaded to an increase in utilization at the more popular charging stations. The point costs setting is a trade-off between customer acceptance and utilization distribution.

Furthermore, we decreased the start and maximum points and tested its effects on the utilization distribution. The reduction of the maximum points affects the maximum reserve time of a Type-2 or Type-3 charging station. At 100 points, the maximum duration is ~ 8.25 h for a Type-2 and 5 h for a Type-3 station. We halve both the starting and maximal points, which leads to a maximal duration of ~ 4 h for Type-2 and 2.5 h for Type-3 stations. An average charge in 2021 was ~ 4.5 h. In order to direct the system to attempt redistributing the long charging sessions to the less popular charging stations, we recommend setting the maximum points in a way that the longest reservation duration at a Type-3 charging station is less than 4.5 h. Applying this configuration does not lead to substantial utilization changes. However, the setting prevents the attractive stations from being reserved from one EV driver for the whole time. In order to simulate the predicted increase of EV charging processes within the cities and urban areas, we took the utilization data from 2021 and doubled all charging processes. Therefore, we assume that at one certain EV charging station at one time slot the existing charging processes including its charging duration are required twice.

Figure 9 depicts the effects on the utilization distribution considering a doubled number of charging processes. The results reveal that the utilization rates of the charging stations converge with a larger number of charging processes, which is one central objective of the solution. Based on these results, we assume that the introduced distribution method is scalable and may be applied in scenarios, in which the number of EVs is increasing.

4.3 Integrating the Approach Into a Mobile App

For demonstrating the applicability and feasibility of the utilization distribution method, we integrated it into a mobile web app. Therefore, we applied the open source web framework Ionic, which is based on HTML, CSS, JavaScript/TypeScript and integrates the front-end web application framework Angular. Ionic can be applied to build hybrid apps that can be designed for smartphones or desktops. For the map view, Google's Map JavaScript API is used, while the charging station operator provides the geographical locations of the EV charging stations.

For guiding the app user through the reservation steps, we developed a reservation process, which is depicted in Fig. 10. We provide the relevant GUIs of the activities via Zenodo (# 6973573). Reserving a charging station is possible after the user registers a profile, which is necessary to manage his scores and charging card number to unlock the charging station. Once the user is logged in, he can access his score and his profile. In the profile, he can overview his current and past reservations. He also has the option to cancel a reservation he made before.

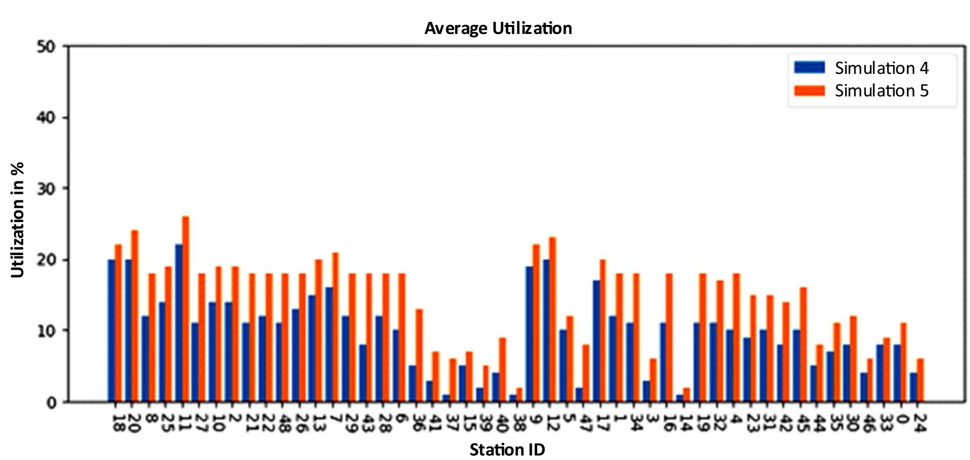
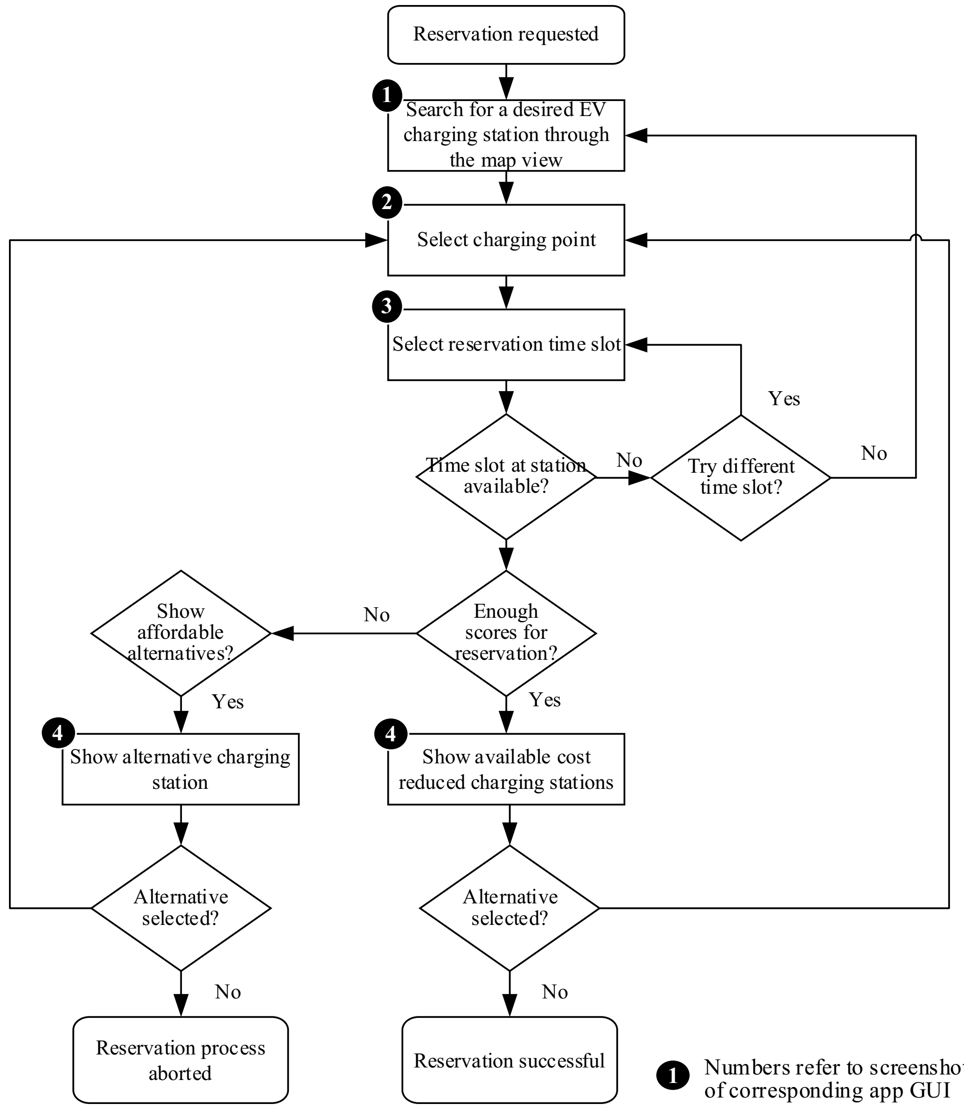


Fig. 9 Utilization distribution when doubling the charging processes

Fig. 10 App reservation process



The process begins with a reservation request. All charging stations in scope are depicted on the Google map with its number. In addition, the map view enables searching for nearby charging stations as well as filtering the results, which fulfils one objective of the solution (cp. Table 1). When the user selects a charging station, he may click on the "Reserve" button in the information view to begin the reservation process. The information view contains additional information about the charging station, which includes information on the costs of the individual utilization levels and the utilization of the charging point, divided into days of the week and time period.

Once the user has decided to reserve a charging station, he is prompted to specify the desired period for his reservation and can do so via the integrated calendar. If the user has enough points for the reservation, it appears in the calendar after the time selection, when the selected timeframe does not overlap previous reservations.

If the user does not have enough points for the desired period, the reservation system offers to search for possible alternatives. If the user decides to look for alternative charging stations, he will be directed to the page, which shows other affordable charging stations nearby. If the user is satisfied with his selection and wants to continue, he may reserve the charging station in the last step. After a successful booking, the reservation appears in his profile as well as in the calendar of the charging station. Thus, no other user can reserve the same period for the chosen charging station.

In the backend, we work with a MySQL database, whose schema is depicted in Fig. 11. In total, we designed five entity types to fulfil the functional requirements and to integrate the utilization distribution approach described in Section 4.2.

The core entity type is the station, which keeps all information about the managed charging stations, including the costs, address, type of power supply, utilization etc. Each time, when the distribution approach recalculates the utilization of a charging station, the data is stored directly at the station entity. Every registration leads to the generation of a new users entity, which is related with upcoming and historical reservation events. The entity type events_history comprises all past reservations and cancelations. It is related to the charging points entity type, which represents the charging opportunities of one station. It is important to note that one charging station may have more than one charging points, whereas one (historic) event is related to exactly one charging point. One charging point may be related to many reservation events.

5 Discussion and Outlook

In this study, we follow the design science research paradigm [11, 13, 28] in order to investigate whether a reservation system for EV charging stations may improve the distribution of charging station utilization. For this purpose, we first conducted interviews with EV drivers and an EV charging station operator, which reveal requirements and the main selection criteria for charging stations. Based on the findings, a point system without using monetary incentives was developed that distributes station reservations and aims at flattening the overall utilization of the charging stations in scope. The system enables EV drivers to reserve EV charging stations and requires the EV driver to reserve proposed alternative charging stations to get a reward for accepting less attractive stations. In turn, the rewarded points

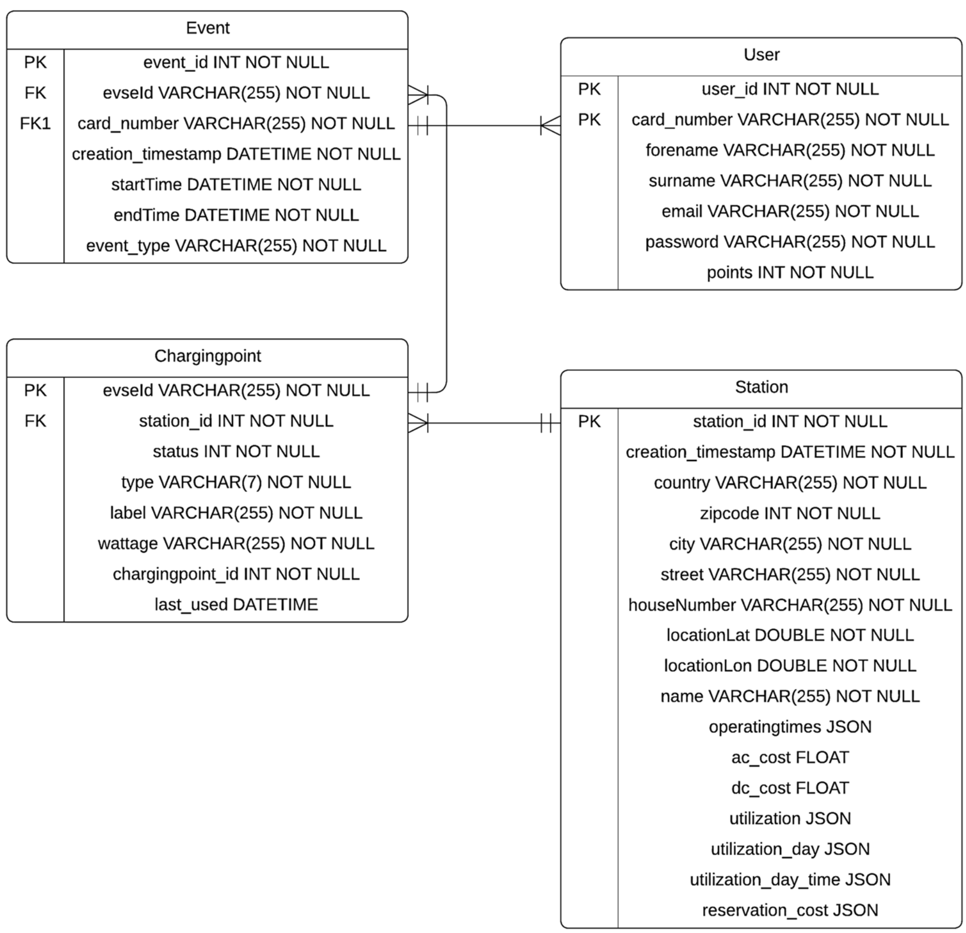


Fig. 11 Database schema

enable the reservation of higher-utilized and more attractive charging stations. Finally, we implemented the system into an app prototype. In order to evaluate it, we conducted simulations based on real charging station data from a large city in Germany. The simulations provide promising results for the redistribution of charging requests and a reduction in average utilization.

Analog to Thompson and Richardson [32], who could show that shorter parking times in inner cities lead to more drivers parking in the peripheral areas of the cities, our approach also reduce the maximum parking reservation time. Since the most utilized charging stations are usually located in the city centres, our system shifts EV drivers to stations located in the suburbs. So far, flattening the charging station utilization is mostly reached by applying monetary incentives [7, 19, 38]. Our interview results clearly revealed that the distance to the final destination of the EV driver is the most influencing factor. The price plays a rather minor role, which indicates that changing the price will most likely have fewer effects on the utilization distribution. For sure, the price may be set to a level, which prevents a reservation for most of the EV drivers. However, this would probably lead to a rejection of the system.

In contrast to the ideas of Eckhoff, et al. [8], who propose offering an EV driver all options when choosing parking spaces and to apply monetary incentives for distributing the utilization, we applied a point-based system. EV drivers are not given the option to choose freely from all charging stations. Instead, they must reserve alternative and probably more unattractive stations to earn points, which then open up more reservation options. The same approach is also used by Kizilkaya, et al. [15], who always search for the closest location in their parking management system. When analysing the real world charging station utilization data, we noticed that the most utilizations take place at solely some few stations. However, even a point-based system must be configured to its environment. The optimum number of points depends on different factors, such as the density of stations and EV drivers in one region. In regions, which have just a few available charging stations but many EV drivers, the parameters must limit the reservation opportunities even more than in areas with enough EV charging stations.

The research contribution of this paper is threefold. First, we provide requirements for the development of an EV charging station reservation system including requirements for a utilization distribution approach. Second, we provide and discuss the modelling of a suitable reservation distribution approach and its instantiation through a mobile app. Third, based on real world utilization data of EV charging stations, we simulate the effects of the utilization distribution approach and provide insights into its applicability. In total, five iterations reveal challenges and possible solutions, which may be a blue print for similar development projects in research and practice.

We worked as rigorous as possible to get the results of this study. However, the results are not free of limitations. First, we conducted five interviews with EV drivers and one interview with an innovation manager of a charging station provider. Thus, the representability of the elicited requirements are limited. Second, the simulation data stem from the years 2020 and 2021. During this time period the Covid pandemic most probably bias the charging behaviour of the EV drivers. We expect much more charging processes in the following years, which to some extent effects the transferability of the simulation results. Third, we did not conduct a field study with the reservation prototype, which means that the impact of the system and its scalability in a real-world setting are not measured so far.

The work at hand reveals a new approach for addressing the challenge of a steadily increasing number of EVs in large city centers and the resulting problems concerning the charging infrastructure. However, further research is needed to provide more evidence. From a behavioural science perspective, we recommend to gain more insights into the requirements for a distribution method, particularly the influence of distance, waiting time and utilization rate on the selection behaviour of EV drivers needs to be investigated. Based on our results, a quantitative study would enhance the validity of the presented requirements. To evaluate the effects of the distribution approach on the utilization, a field study is needed. From a design science perspective, more insights about the applicability of the prototype is necessary. Particularly, the developed database scheme and the app process model leave room for improvement.

Appendix

Table 7 Average utilization per weekday in percent

ID	No Simulation							
	mo	tu	we	thu	fr	sa	su	Avg
0	9	9	10	8	10	9	9	9
1	12	14	15	12	13	8	13	12
2	18	18	20	21	20	23	19	19
3	3	4	3	3	3	1	1	2
4	1	1	1	1	1	1	1	1
5	13	11	10	12	12	12	4	10
6	2	3	2	3	2	0	0	2
7	25	25	28	30	32	30	26	27
8	7	5	5	6	8	7	4	6
9	39	39	37	40	38	39	39	37
10	42	41	42	40	42	41	37	39
11	32	30	34	36	33	37	19	30
12	40	41	39	36	36	39	34	36
13	30	31	32	32	34	31	31	30
14	1	2	1	2	2	1	0	1
15	7	7	7	8	4	0	0	5
16	10	8	9	10	9	6	7	8
17	35	39	39	33	34	34	36	34
18	43	43	41	42	47	45	38	41
19	20	20	21	19	20	6	5	15
20	42	39	40	39	42	52	46	41
21	6	5	6	6	6	6	5	5
22	12	12	13	13	12	10	10	11
23	9	9	9	9	9	9	11	9
24	3	3	4	3	5	6	7	4
25	37	38	37	36	36	40	32	35
26	27	30	31	30	25	23	22	26
27	3	2	2	2	2	2	1	2
28	15	14	13	14	14	12	10	13
29	11	11	11	12	15	15	10	12
30	7	7	8	8	8	9	9	8
31	16	18	17	19	17	8	7	14
32	9	8	8	9	10	10	9	9
33	10	9	10	10	12	14	1	9
34	9	6	9	7	12	1	1	6
35	10	10	9	9	9	5	4	8
36	1	1	1	1	1	0	0	1
37	1	1	1	1	1	0	0	1
38	2	1	1	1	1	0	0	1
39	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0
42	7	6	7	7	6	8	11	7
43	0	0	0	0	0	0	0	0
44	1	3	2	2	3	2	2	2
45	4	4	5	5	5	6	6	5
46	3	2	3	3	4	5	5	3

Table 7 (continued)

ID	No Simulation							
	mo	tu	we	thu	fr	sa	su	Avg
47	1	1	1	2	1	2	3	2
48	7	8	6	7	5	1	1	5
ID	Simulation 1							
	mo	tu	we	thu	fr	sa	su	Avg
0	8	8	9	8	9	8	8	8
1	16	17	19	15	17	15	15	16
2	13	14	15	15	14	16	13	14
3	3	4	3	4	4	1	2	3
4	7	6	7	7	7	2	2	5
5	12	11	10	12	12	12	5	10
6	11	11	11	11	11	9	8	10
7	17	16	17	19	18	18	15	16
8	12	12	13	13	14	12	11	12
9	19	20	19	20	20	20	19	19
10	18	18	19	18	20	21	16	18
11	30	29	31	31	32	34	21	29
12	21	22	21	21	21	24	17	20
13	15	15	17	15	17	15	15	15
14	1	2	1	2	2	1	0	1
15	7	7	7	8	4	0	0	5
16	11	10	11	11	11	9	9	10
17	17	20	20	17	19	18	16	17
18	21	21	21	21	24	24	18	21
19	17	18	19	18	19	7	5	14
20	19	19	20	19	21	27	21	20
21	13	12	13	12	13	13	13	12
22	17	18	17	18	17	16	16	16
23	9	9	9	8	8	8	10	8
24	3	3	4	3	5	6	7	4
25	20	21	20	21	22	26	17	20
26	16	18	20	19	17	17	19	17
27	12	11	11	11	11	10	9	10
28	17	16	15	16	17	14	13	15
29	16	17	16	17	19	19	15	16
30	7	7	8	8	8	9	9	8
31	14	15	14	15	13	7	7	12
32	9	8	8	9	10	10	9	9
33	10	9	10	10	12	14	1	9
34	12	10	13	12	12	9	10	11
35	9	9	9	8	8	5	4	7
36	6	5	5	6	5	4	3	5
37	1	1	1	1	1	0	0	1
38	2	1	1	1	1	0	0	1
39	1	1	2	1	1	1	1	1
40	2	3	2	2	2	2	2	2
41	0	0	0	0	0	0	0	0
42	7	6	8	7	8	8	11	8
43	11	12	11	11	12	9	8	10
44	5	7	6	6	7	3	3	5

Table 7 (continued)

ID	No Simulation							
	mo	tu	we	thu	fr	sa	su	Avg
45	7	8	9	10	9	7	6	8
46	3	2	4	4	4	5	5	4
47	2	2	2	2	2	2	3	2
48	13	14	14	14	15	13	11	13
ID	Simulation 2							
	mo	tu	we	thu	fr	sa	su	Avg
0	7	7	8	7	7	6	7	7
1	12	12	12	10	11	8	10	10
2	11	12	12	12	10	12	12	11
3	5	6	5	6	5	4	5	5
4	9	6	8	9	8	7	6	7
5	9	8	8	9	8	9	5	8
6	8	9	9	9	8	8	8	8
7	14	15	16	18	17	16	14	15
8	10	10	10	10	9	9	10	9
9	18	19	19	19	19	19	18	18
10	14	14	14	13	15	16	13	14
11	22	21	24	24	22	25	13	21
12	20	20	20	20	20	22	16	19
13	12	13	14	13	14	12	13	13
14	4	5	4	4	4	3	1	3
15	5	7	7	7	5	2	1	5
16	9	9	9	9	9	8	8	8
17	16	19	19	15	18	16	15	16
18	20	20	20	19	23	22	16	19
19	12	11	13	11	11	6	7	10
20	17	17	20	18	19	26	20	19
21	10	10	11	10	9	9	10	9
22	11	12	12	12	11	10	10	11
23	7	7	7	7	7	6	8	7
24	5	5	5	5	5	5	5	5
25	14	14	15	14	15	19	12	14
26	12	12	14	13	11	11	12	12
27	8	9	9	9	8	8	9	8
28	12	11	11	11	10	9	10	10
29	11	11	11	12	12	13	10	11
30	6	6	7	6	6	7	7	6
31	10	12	11	12	10	6	6	9
32	8	7	7	9	9	9	8	8
33	8	7	8	8	9	11	4	8
34	9	10	10	10	9	7	8	9
35	7	7	7	7	7	5	5	6
36	8	8	9	8	7	7	8	8
37	4	5	5	5	5	4	0	4
38	4	4	3	4	4	2	0	3
39	5	3	2	2	5	2	2	3
40	7	5	5	6	7	5	4	5
41	7	6	6	6	7	7	3	6
42	8	7	8	8	7	7	9	7

Table 7 (continued)

ID	No Simulation							
	mo	tu	we	thu	fr	sa	su	Avg
43	8	9	9	9	8	8	8	8
44	5	7	6	6	7	4	4	5
45	7	8	8	8	8	7	6	7
46	5	5	6	6	6	6	5	5
47	5	5	5	6	5	5	6	5
48	8	9	10	9	8	8	8	8
ID	Simulation 3							
	mo	tu	we	thu	fr	sa	su	Avg
0	8	8	9	8	10	9	9	8
1	13	12	13	13	13	10	10	12
2	13	12	13	13	13	12	11	12
3	3	4	3	3	3	2	2	3
4	12	12	12	10	13	9	9	11
5	12	12	11	12	12	10	5	10
6	13	12	12	13	12	10	10	11
7	14	14	16	18	17	16	13	15
8	13	13	13	13	13	12	10	12
9	18	19	18	19	19	20	18	18
10	14	15	15	15	16	17	14	15
11	21	19	22	23	21	24	11	19
12	20	21	19	19	19	22	15	19
13	13	13	14	13	15	13	12	13
14	1	2	1	2	2	1	0	1
15	7	7	7	8	4	0	0	5
16	12	12	12	12	13	10	10	11
17	15	20	19	15	17	16	14	16
18	20	20	19	19	24	23	16	19
19	13	12	13	13	12	10	10	11
20	17	17	19	18	19	27	20	19
21	13	12	12	13	13	10	10	11
22	13	12	13	13	13	11	10	12
23	9	9	9	10	9	8	10	9
24	3	3	4	3	5	6	6	4
25	14	14	16	15	15	19	11	14
26	13	13	14	14	13	13	11	13
27	13	12	12	13	12	10	10	11
28	13	12	12	13	13	11	10	12
29	13	12	13	13	13	13	10	12
30	7	7	8	8	8	9	9	8
31	13	13	12	13	12	7	7	11
32	12	12	12	13	12	10	10	11
33	10	9	10	10	11	13	1	9
34	13	12	13	13	13	10	10	12
35	9	9	8	8	8	5	4	7
36	9	9	8	8	8	9	8	8
37	1	1	1	1	1	0	0	1
38	2	1	1	1	1	0	0	1
39	1	1	1	1	1	1	1	1
40	4	5	3	4	4	4	4	4

Table 7 (continued)

ID	No Simulation							
	mo	tu	we	thu	fr	sa	su	Avg
41	0	0	0	0	0	0	0	0
42	7	7	8	7	8	8	10	8
43	13	12	12	13	12	10	10	11
44	4	7	6	6	5	2	2	4
45	9	12	12	12	11	7	7	10
46	3	2	3	3	4	5	5	3
47	1	2	2	2	1	2	3	2
48	13	12	13	13	13	10	10	12
ID	Simulation 4							
	mo	tu	we	thu	fr	sa	su	Avg
0	7	7	8	8	9	8	8	8
1	12	12	12	12	13	10	10	11
2	13	14	14	14	14	14	12	13
3	3	4	3	3	4	2	3	3
4	11	11	12	11	12	6	9	10
5	11	10	10	11	11	10	6	9
6	10	11	8	11	9	10	8	9
7	15	15	16	18	18	16	14	15
8	12	12	12	12	13	12	10	11
9	18	19	18	19	19	20	18	18
10	14	14	15	14	15	16	12	14
11	22	21	23	25	23	25	13	21
12	20	21	20	20	20	23	16	19
13	14	15	16	15	16	14	13	14
14	1	2	1	2	2	1	0	1
15	7	7	7	8	4	0	0	5
16	12	11	12	12	12	10	9	11
17	16	19	19	15	18	16	15	16
18	20	20	20	19	24	23	16	20
19	11	12	13	11	12	10	9	11
20	18	17	20	19	20	27	20	19
21	12	12	12	12	13	10	9	11
22	12	12	12	13	13	12	10	12
23	9	9	9	10	8	8	9	9
24	3	3	4	3	5	5	5	4
25	13	14	15	14	15	18	11	14
26	13	13	14	13	13	12	11	12
27	12	11	12	12	11	10	9	11
28	13	12	12	13	13	11	10	12
29	12	12	12	13	14	14	10	12
30	8	8	9	8	9	9	8	8
31	11	13	11	12	11	7	7	10
32	11	12	12	12	12	10	8	11
33	9	9	9	9	10	11	1	8
34	12	11	12	12	13	9	9	11
35	9	9	8	8	8	5	4	7
36	6	6	5	6	5	5	5	5
37	2	2	1	1	2	1	0	1
38	2	1	1	1	1	0	0	1

Table 7 (continued)

ID	No Simulation							
	mo	tu	we	thu	fr	sa	su	Avg
39	2	2	2	1	1	1	2	2
40	5	5	4	4	4	4	5	4
41	4	4	3	3	4	3	3	3
42	7	7	8	8	8	8	10	8
43	6	8	7	8	7	10	8	7
44	5	8	7	6	6	3	2	5
45	10	11	11	12	12	7	7	10
46	4	2	4	3	4	6	5	4
47	2	2	1	2	2	3	3	2
48	12	12	12	12	13	10	9	11
ID	Simulation 5							
	mo	tu	we	thu	fr	sa	su	Avg
0	10	10	11	10	12	13	13	11
1	19	18	19	19	20	18	16	18
2	19	19	20	20	20	18	17	18
3	6	8	7	7	8	4	4	6
4	18	18	18	19	19	15	16	17
5	14	12	12	14	14	13	6	12
6	18	18	19	19	19	17	15	17
7	20	21	21	23	23	21	18	20
8	19	18	18	19	20	18	16	18
9	23	21	22	23	23	22	20	21
10	19	18	19	19	20	19	16	18
11	27	25	28	29	28	30	17	25
12	23	23	23	23	24	24	19	22
13	19	20	21	21	21	18	17	19
14	2	2	2	3	3	1	0	2
15	11	11	11	10	6	0	2	7
16	18	18	18	19	19	16	15	17
17	20	20	22	20	22	20	17	19
18	22	22	22	22	26	25	18	22
19	18	18	18	19	19	17	15	17
20	23	22	23	24	24	29	21	23
21	18	18	18	19	19	17	16	17
22	18	18	19	19	20	17	16	17
23	14	15	15	15	15	12	16	14
24	5	5	5	4	7	7	7	5
25	19	19	20	19	20	22	16	19
26	19	18	19	19	20	18	16	18
27	18	18	18	19	19	17	16	17
28	19	18	19	19	20	17	15	17
29	18	18	19	19	20	18	16	18
30	11	11	12	12	13	13	11	11
31	16	16	16	16	16	11	12	14
32	18	17	17	18	19	17	15	17
33	10	10	10	10	12	12	2	9
34	18	18	19	19	20	17	16	17
35	13	13	12	12	12	9	7	11
36	13	14	13	13	14	13	10	12

Table 7 (continued)

ID	No Simulation							
	mo	tu	we	thu	fr	sa	su	Avg
37	8	8	7	7	5	4	4	6
38	4	3	2	2	2	0	0	2
39	6	6	5	4	4	4	5	5
40	9	10	9	9	9	8	8	9
41	7	8	7	7	7	7	7	7
42	14	13	16	13	14	12	15	13
43	18	18	19	18	19	17	15	17
44	7	11	10	9	10	6	4	8
45	16	17	17	18	18	16	13	16
46	6	4	6	6	6	8	7	6
47	10	8	8	7	7	9	10	8
48	18	18	19	19	19	17	15	17

Abbreviations CSS: Cascading style sheets; EV: Electronic vehicle; GUI: Graphical User Interface; HTML: Hypertext Markup Language; OCPP: Open Charge Point Protocol; Util: Utilization

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Declarations

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