Renewable and Sustainable Energy Reviews 185 (2023) 113600

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Original research article

Assessing the value of information for electric vehicle charging strategies at office buildings

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ARTICLE INFO

Keywords:
EV charging behavior
Electric vehicles
Smart charging
Statistics
Parking lot
Value of information

ABSTRACT

Smart charging strategies for electric vehicles (EVs) require as input information such as energy requirement and dwell time. In practice, that information is often not available. However, estimations may be obtained from historical charging behavior. This paper investigates the added value of historical information for EV charging strategies based on real-world EV charging data collected in an office building parking lot with 125 chargers. Furthermore, it provides valuable insights into EV charging behavior at office building parking lots, based on a statistical analysis of the data. The added value of data availability in EV charging strategies for day-ahead planning and real-time operation of office building parking lots is assessed via a set of quality metrics that measure user satisfaction and impact on the local grid. Offline charging strategies under various degrees of available information are validated by comparing their performance with the real-time operation of the parking lot. Results show a power peak reduction of more than 50% using historical data and simple estimations of arrival times, dwell times, and energy requirement. A trade-off between power peaks and service quality (on average 4.4 kWh energy not served) is observed. It was found that knowledge of individual average energy provides higher added value compared to knowing individual average dwell time in both offline planning and real-time operation of the parking lot.

1. Introduction

Integration of electric vehicles (EVs) into the electrical grid comes with challenges due to their high power and energy consumption. On top of that, the grid infrastructure is designed based on long term estimates for demand growth, which some years ago, did not consider the deployment of newly emerging consumption and generation technologies, such as EVs, heat pumps or solar panels (PVs). In that sense, the grid is not prepared to facilitate the rapidly growing power demand posed by EVs [1]. Particularly in residential neighborhoods, technical constraints such as voltage, current, or transformer capacity are expected to be infringed regularly in the future due to the integration of these new technologies [2]. Furthermore, capacity limitations are paired with synchronization effects [3] and mismatches between local solar PV generation and peaking EV charging demands [4].

One approach to tackle the mentioned issues is smart charging. Smart charging is a control strategy that based on data inputs, supports the decision-making of individual chargers to guarantee the proper operation of the whole system. This indicates that smart charging relies heavily on information availability. While information related to global grid constraints like power capacity is available, information on the individual EV constraints is usually missing [5]. However, that information is difficult to predict due to highly uncertain user behavior. Furthermore, it is also not always accurate when communicated via EV apps or internet of things (IoT) systems. This makes EV charging plannings less reliable when deployed in real-time.

Parking lots at office locations have been identified to hold great potential for smart charging due to the homogeneous population and the relatively long parking times during the day [6]. This paper focuses on using historical information collected at an office parking lot to investigate the value of information on arrival times, dwell times and energy requirements, and how past information reflects operational realities.

1.1. Related work

Smart charging schemes in literature often assume perfect information on, among others, the initial state of charge (SOC) or when EVs are available to charge (dwell time), see for example [7–10]. Saldaña et al. [11] provide a comprehensive overview of studies on EV smart charging and their respective assumptions. It has been shown

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https://doi.org/10.1016/j.rser.2023.113600
Received 22 December 2022; Received in revised form 19 July 2023; Accepted 28 July 2023
Available online 14 August 2023

Nomenclature

Abbreviations

AIC	Aikaki information criterion
BIC	Bayesian information criterion
CDF	Cumulative distribution function
EV	Electric vehicle
GMM	Gaussian mixture model
IGDT	Information gap decision theory
IoT	Internet of things
PDF	Probability distribution function
PV	Photo voltaic
SOC	State of charge

List of Symbols

Δ_t	Size of time step $t \in \mathcal{T}$
$\mathcal{T}$	Discrete time horizon $\{0, \dots, T\}$
μ^x	Mean of x, $x \in \{at, dt, dwt\}$
σ^x	Variance of x, $x \in \{at, dt, dwt, e\}$
E_i^x	Energy supplied to EV i in profile $x \in \{0, plan, real\}$
ENS^x	Average energy not served in profile $x \in \{plan, real, mismatch\}$ [kWh]
ens^x	Average relative energy not served in profile $x \in \{plan, real, mismatch\}$ [%]
$ENS_i^{mismatch}$	Energy not served to EV i in real-time operation compared to offline planning [kWh]
ENS_i^x	Energy not served to EV i in profile $x \in \{plan, real\}$ [kWh]
ens_i^x	Relative energy not served to EV i in profile $x \in \{plan, real, mismatch\}$ [%]
ENS_{max}^x	Maximum energy not served in profile $x \in \{plan, real, mismatch\}$ [kWh]
ens_{max}^x	Maximum relative energy not served in profile $x \in \{plan, real, mismatch\}$ [%]
EV	Set of simulated EV population $\{1, \dots, n\}$
n	Total number of simulated EVs
$P^x(t)$	Aggregated power profile at time $t \in \mathcal{T}$ in profile $x \in \{0, plan, real\}$
$P_i^x(t)$	Power profile of EV i at time $t \in \mathcal{T}$ in profile $x \in \{0, plan, real\}$
$P_{max}^x(t)$	Maximum aggregated power peak in profile $x \in \{0, plan, real\}$

Superscripts

0	Baseline scenario
at	Arrival time
dt	Departure time
dwt	Dwell time
e	Energy demand
$mismatch$	Concerning comparison between planning and real-time operation
$plan$	Concerning offline planning
$real$	Concerning real-time operation

that information on the SOC of an EV battery is crucial information for charging strategies [12], however that information is usually not available in practice.

The authors in [13,14] claim that smart charging strategies depend on EV user preferences (e.g., planned departure time and desired SOC), which need to be estimated or directly communicated to the charging operator to control and optimize (public) EV charging. Hereby, these studies focus on the impact of different charging interfaces in the adoption of smart charging strategies or the effect of communicating minimum load versus minimum energy requirements, which contributes to understanding user behavior. However, the value of information in the planning and real-time operation of an office building parking lot is not assessed. Other works focus on the effect of information sharing on pricing mechanisms for coordinated control, see for example [9,15,16]. Those models are proven to help alleviate operational issues in electrical grids, however, parking lots or aggregators might have interests other than grid balancing.

Some research has been done into filling information gaps with direct EV driver input using mobile apps [9,17,18]. The advantage of this lies in its ability to acquire information in advance, without the need for EV-to-charger communication, which currently is not implemented by default. However, such approaches require active user participation, and it was found that users tend to overestimate energy requirements. None of the listed studies targets users in office locations. Liu et al. [19] simulate an office location with local solar generation where drivers communicate charging preferences in a financial incentive-based transaction model. However, in [20], it was found that when adopting smart charging, filling the battery with enough energy to serve mobility needs is more important than monetary incentives.

One approach to address uncertainties in an energy system is to take an aggregated perspective, as in the valley-filling approach [21], where authors demonstrated that using fill-level-based real-time control is a robust approach for load balancing. Using aggregated profiles offers advantages such as preserving data privacy and reducing the computational burden, at the expense of losing accuracy and not meeting individual preferences.

Other approaches use Information Gap Decision Theory (IGDT) to handle uncertainties of energy prices in EV charging [22,23]. Although IGDT provides robust framework to handle uncertainties focusing on worst-case scenarios without the need for precise data, uncertainties related to EV user behavior were disregarded in this work. In contrast, [24] proposes a hybrid stochastic/IGDT optimization technique for EV charging/discharging in an office building which uses a scenario-based model to handle uncertainties in arrival time, departure time, and initial SOC. However, the authors do not assess the robustness of their model in a real-time EV charging scenario. Moreover, they assume direct communication between EV users and charging infrastructure, which is not realistic given current implementations. Simolin et al. [25] studied communication requirements with regard to the value of information that can be obtained during real-time EV charging control. Their study focuses on estimating the maximum charging power under non-ideal EV response and the approach is validated using real data and measurements collected at a shopping center. The advantage of a measurement-based charging control is that no information from the EV is required. However, while historical data is used to estimate the maximum power, the use case in the shopping center does not allow for individual EV analysis, but instead takes an observed average of similarly behaving EVs in the past.

Some studies have shown the great potential of near office parking locations to fill afternoon-valleys in local energy profiles due to the relatively long dwell time of EVs [6] and to provide ancillary services when combined with local solar generation [26]. A comprehensive review on the integration of solar rooftop parking lots with EV charging is presented in Osório et al. [27].

Although many papers on potential smart charging approaches exist, using historical data of EV charging sessions to validate and test these approaches is scarce [28]. While there are studies simulating smart charging of parking lots using real-world data [29–31], their scale is limited to parking lots hosting less than 30 chargers and are in public spaces or a university campus, rather than office buildings.

On the other hand, various studies to statistically analyze EV charging data exist [32–35], among others investigating sample distributions and characterizing session and user types of EVs. However, none of those studies focuses on office parking lots, but rather study public charging stations. Moreover, Andersen et al. [36] found that each EV driver has particular driving needs and preferences and therefore statistical representations of individual behavior may be more appropriate for flexibility provision while fulfilling driving requirements for EV users. To compensate for the limited amount of available real-world data, there is on-going research into synthetic data generation tools [37]. Using this data, simulations at large scale can be run (e.g., [38,39]). However, the achieved results have to be treated with care as a ground truth validation with realistic data is missing. To the authors' best knowledge, there is no data available yet that describes charging sessions at a large-scale office parking lot, considering both employees and visitors. In addition, COVID-19 had a substantial impact on observed charging data [40], which is not yet reflected in the data sets cited here.

1.2. Main contributions

This paper investigates the added value of data availability in EV charging strategies for day-ahead (offline) planning and real-time operation of office building parking lots. Historical EV charging sessions collected in an office building parking lot in the Netherlands are used to characterize the EV charging behavior. The main scientific contributions of this paper are:

- Statistical insights into a unique real-world data set concerning the EV population and its charging at an office building in the Netherlands. This is useful for researchers involved in design processes such as sizing of parking lots (e.g., EV charging and local electricity grid components), development of EV charging strategies, and EV flexibility quantification in future office parking lots.
- A set of quality metrics to measure satisfaction from the user perspective (based on energy not served) and from the grid operator perspective (power peaks in the local grid) and an assessment of the added value of historical information in EV charging strategies.
- Validation of the performance of offline EV charging strategies under different degrees of available information at an office building parking lot using DEMKit, a toolkit to control and optimize cyber–physical energy systems.

The remainder of the paper is organized as follows. First, Section 2 presents the data set used in this research. Afterward, the methods used to simulate EV charging at office buildings and to validate the performance of charging strategies under different degrees of available information are presented in Section 3, followed by the obtained results in Section 4. The paper ends with a discussion of the main findings and conclusions (Sections 5 and 6).

2. Analysis of office building EV charging sessions

This section provides a statistical analysis of the available data set collected at an office building in the Netherlands. First, this data set is described in Section 2.1, followed by a global and individual data analysis. Based on this, a characterization of EV charging sessions in office buildings is given using a clustering algorithm based on a Gaussian mixture model (GMM). Hereby the proposed approach to analyze the data set is independent of the data input and can be used also with other data sets containing similar information.

2.1. Description of the data set

This paper uses real-world data collected from January 1st, 2020 to August 31st, 2022 at a physical pilot site at an office building in Utrecht, the Netherlands. The office has a parking lot that will eventually host 383 AC EV chargers (22 kW), 66 DC EV chargers (10–50 kW), a PV rooftop installation with a total capacity of 951 kWp, and a 172.8 kWh battery storage. Currently, approximately 125 chargers are in operation. The parking lot has a local energy management system that registers all EV charging sessions. However, at this moment no smart charging strategies are applied. The data set contains the session ID, user ID, arrival time, departure time, and total energy supplied per session, making it possible to look into patterns of individual users. The parking lot is open to both employees and visitors of the office building with designated areas for each group.

Various functional tests were conducted at the pilot site over the data collection period, resulting in atypical data points that were filtered out.[1] Charging sessions that lasted less than 10 min, more than 24 h, or charged less than 1 kWh over the session were filtered out. Furthermore, during an initial period, a plug-and-charge charging mode was available, during which some sessions were registered using a generic user ID. Those data points were also removed from the data set.

The resulting data set consists of 7565 charging sessions associated with 625 individual charging IDs. A maximum of 102 charging sessions was registered in a single day.

2.2. Global data analysis

A statistical analysis of aggregated charging sessions at the parking lot is performed in order to gain general insights into the usage of the parking lot. The daily utilization of the parking lot and the aggregated charging behavior are characterized using probability distribution functions (PDFs) and cumulative distribution functions (CDFs), using four main parameters observed in the data set: arrival time, departure time, dwell time, and energy demand.

Fig. 1 shows the monthly energy delivered in the parking lot during the analyzed period. Note that low energy was delivered during the first year (July 2020 to July 2021), when most employees worked from home due to the COVID-19 lockdown. In June 2021, the lockdown was lifted, resulting in increased energy delivered, reaching a peak of around 3 MWh in September 2021. After that period and until January 2022, the parking lot's usage was again affected due to a lockdown. Since then, the parking lot has been continuously operational, as can be seen by the continuous increase in the monthly energy delivered.

Fig. 2 shows the week-day utilization of the parking lot during the analyzed period. Figs. 2(a) and 2(b) show the daily amount of charging sessions and energy demand per session, respectively. It can be seen that the parking lot is busiest on Tuesdays with approximately 25 charging sessions per day. The highest average energy requirement (>30 kWh) is observed during the weekend although those days register only a few charging sessions per day. This happens because during the weekend the parking lot is available to non-employees.

Fig. 3 shows statistical information on the four main parameters chosen to characterize EV charging behavior at the parking lot. Hereby, the mean (μ^x) and standard deviation (σ^x) for each parameter x are given.

For the arrival time (at), Fig. 3(a) suggests that overall EV users arrive around the same time interval. The PDF is statistically characterized by $\mu^{at} = 9.4$ h and $\sigma^{at} = 2.23$ h, but does not specifically follow a homogeneous shape. Considering the plot in Fig. 3(b), the PDF seems to be a combination of two different normal distribution functions,

[1] The source code used to process, filter, and statistically analyze the data is available in https://github.com/lwinschermann/OfficeEVparkingLot.

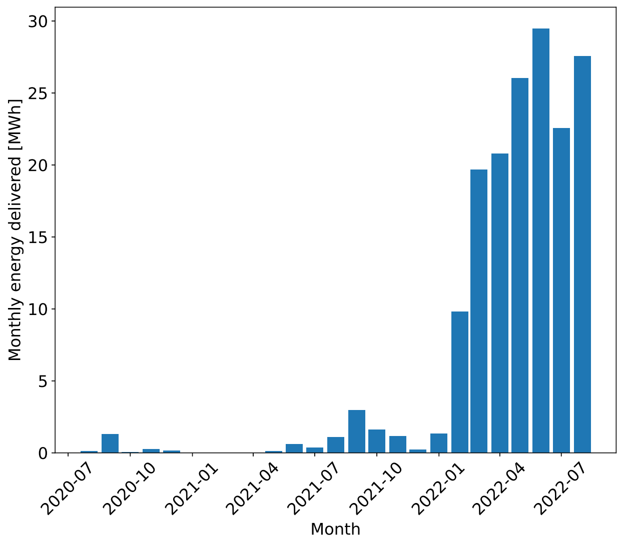


Fig. 1. Monthly energy delivered during the period under analysis.

potentially representing EV users that arrive early in the morning and users that arrive after noon. Furthermore, the CDF (Fig. 3(c)) indicates that 80% of the users arrive before 11:00.

The box-plot of the departure time (dt) (Fig. 3(d)) shows a similar behavior as the arrival time. The PDF shown in Fig. 3(e) is characterized by $\mu^{dt} = 15.8$ h and $\sigma^{dt} = 2.3$ h. Furthermore, in this case one may assume that there are more than two different normal distribution functions, potentially representing EV users that leave in the morning or in the afternoon. Fig. 3(f) indicates that 80% of the users leave before 18:00.

The dwell time (dwt) (Fig. 3(g)) suggests a wider spread for the time the EV users stay at the parking lot. The PDF is represented by $\mu^{dwt} = 6.7$ h and $\sigma^{dwt} = 2.9$ h. However, again the figure indicates two different normal distribution functions may be present (Fig. 3(h)), possibly representing EV users with short and long stays. Fig. 3(i) indicates that 80% of the EVs stay up to 10 h in the parking lot.

The box plot of the energy demand follows a similar behavior as the dwell time, with a wide range of preferences in the energy demand. The PDF follows a different shape given by $\mu^{e} \approx 22$ kWh and $\sigma^{e} \approx 15.6$ kWh, which indicates that the data is widely spread. Fig. 3(l) indicates that 80% of the users require less than 40 kWh.

The correlation among the four parameters was further investigated. As can be seen in Fig. 4, from a global perspective, there is not a strong correlation among the parameters. Note that the departure time and the dwell time are the parameters with the highest correlation, followed by the dwell time and the energy demand. However, these correlation values are not high enough to establish a strong dependency among the parameters. One way to approach this is by grouping the data according to certain characteristics (e.g., clusters) to investigate ground-truth correlation among such parameters and develop sophisticated models for the prediction of EV user behavior at office buildings.

2.3. Individual data analysis

Given the fact that several EV users visit the parking lot, it is interesting to see how different the behavior among EV users is. To this end, an individual analysis for the 10 EVs with the most charging sessions (>60 charging sessions each) is presented.

Fig. 5 shows the mean, minimum, maximum, and 25%, 50%, and 75% percentiles for the arrival time, departure time, dwell time, and energy demand of these users. Most of these EVs have a similar average arrival time around 09:00 (only EV2 arrives around noon). However, note that the area covered by the percentiles around the mean (red line) is different in size for all EVs, meaning that the data variance differs per individual user. Similar behavior is observed for the departure and dwell time. Concerning the individual energy demand of the EVs (Fig. 5(d)), two main behaviors can be observed with one group of EVs demanding around 30 kWh, and the other demanding less than 10 kWh. This may reflect the two different categories of fully electric vehicles and plug-in hybrids or different work-home-commutes of the respective employees. The size of the intervals around the mean also presents huge variations among the users, especially for EV1, EV5, and EV8. These results show that individual user behavior is highly intermittent.

2.4. Clusters analysis

In this section, the charging behavior of users at the office building is investigated using a tri-dimensional clustering approach that considers the arrival time, dwell time, and energy demand of the resulting charging sessions after the filter process described in Section 2.1. The potential charging clusters are identified using a Gaussian mixture model (GMM) clustering approach, a probabilistic model to represent a mixture of multiple Gaussian distributions on population data. This approach decomposes a single data distribution into a number of Gaussian distributions called components. Each component then represents a cluster with the following information: mean, covariance, and weight (probability of occurrence) [41]. The number of clusters to properly represent the user behavior is selected using the Aikaki information criterion (AIC) and the Bayesian information criterion (BIC) [42]. Those models measure how well the GMM fits the data and avoid overlaps between the components.

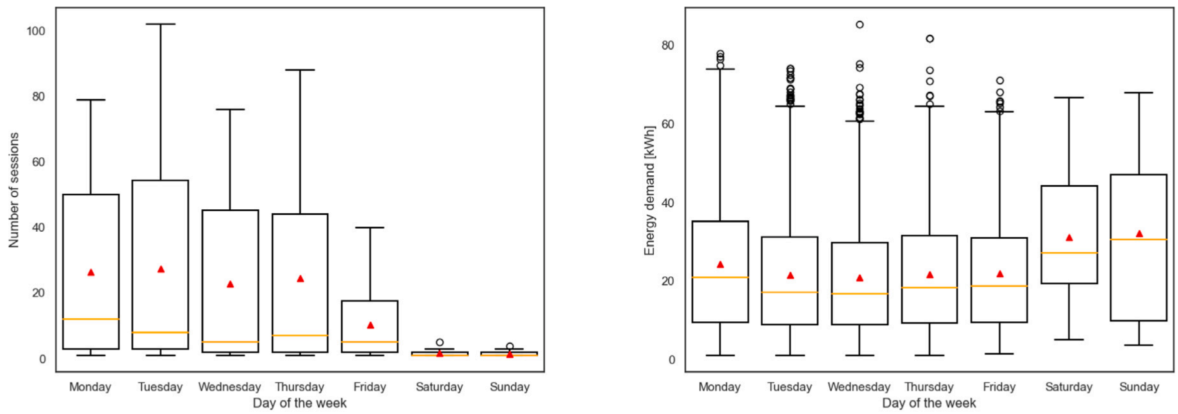
Initially, the distribution of the data is analyzed considering the energy demand and the start time. As shown in Fig. 6(a), the majority of the charging sessions start around 09:00 in the morning with energy demands varying mostly between 10 and 50 kWh. For this clustering approach the BIC and AIC plots in Fig. 6(b) suggest at least 30 clusters (point in the x-axis where the curve becomes stable) to characterize the EV charging behavior at the office building. This high number of clusters is due to the highly variable energy demands in the data set.

A second analysis is performed considering the arrival time and the dwell time instead. As shown in Fig. 7(a), the majority of the charging sessions start around 09:00 and the EVs stay in the parking lot for around 9 h. The BIC and AIC in Fig. 7(b) suggest around 8 clusters to characterize the EV charging behavior at the office building. However, this cluster approach disregards the energy demand feature, which is an important parameter to characterize user behavior in parking lots.

Therefore, a 3D-clustering approach is presented considering arrival time, dwell time, and energy demand. Based on the BIC and AIC (Fig. 8(a)), 13 clusters (Fig. 8(b)) are required to characterize the EV charging behavior in our data set. The characteristics and initial description of the clusters are provided in Table 1.

The high number of clusters illustrates the complexity of categorizing the data. This complexity is mainly due to the energy demand being highly variable as previously shown in Fig. 3(j). However, even with this high number of clusters, one can identify some similarities among the clusters. For instance, when looking at the mean arrival time, Clusters 0–7 group charging sessions with arrival times in the morning. Considering that this is an office building, these clusters likely represent employees at the office. Users that arrive after 12:00 (i.e., Clusters 8–12) could be part-time employees or visitors. Concerning the dwell times, charging sessions with six or more hours are categorized as “long stays”. This category likely represents full-time employees. Charging sessions with a duration between three and five hours are “short stays”. Finally, users that stay less than 3 h are included in the “very short stay” category. It is assumed that they are visitors. Lastly, users that arrive in the afternoon and stay for a long period are categorized as overnight users. They represent a very small number of samples.

Given the variability in the energy demand, a scale for the energy demand is defined, consisting of “low energy” (≤10 kWh), “medium



(a) Daily amount of charging sessions

(b) Daily amount of energy demand

Fig. 2. Daily utilization of the parking lot from July 2020 to July 2021.

Table 1
Temporal-energy clusters at the office building.

Cluster	Mean arrival time	Mean dwell time	Mean energy	Mean departure time	Weight	Number of samples	Description	Energy level
0	8	7	45,34	15	0,04	231	Long stays - Employees	High
1	8	7	29,78	15	0,11	807	Long stays - Employees	Medium
2	8	8	8,01	17	0,17	1485	Long stays - Employees	Low
3	8	9	47,08	17	0,09	747	Long stays - Employees	High
4	9	9	21,74	17	0,16	1343	Long stays - Employees	Medium
5	9	6	13,88	14	0,13	722	Long stays - Employees	Medium
6	11	6	49,07	17	0,03	185	Long stays - Employees	High
7	10	4	8,38	14	0,10	795	Short stays - Employees/visitors	Low
8	12	4	22,16	16	0,08	495	Short stays - Employees/visitors	High
9	12	1	4,55	13	0,02	182	Very short stays - Visitors	Low
10	12	2	24,42	14	0,06	474	Very short stays - Visitors	Medium
11	12	12	57,89	13	0,00	16	Very long stays - Overnight users	High
12	19	16	31,22	10	0,01	83	Very long stays - Overnight users	High

energy” (11–30 kWh), and “high energy” (≥31 kWh). The low and medium energy categories may represent users with hybrid EVs or users that partly charge their EVs at home while the high energy category represents users with fully electric cars that might not charge their EVs at home or live farther away.

Using the introduced scales on the available data, the charging behavior at the office building is categorized into four clusters, each with sub-clusters for the energy level, as shown in Table 2. Note that Cluster 1 has the highest probability of occurrence (72%), which could have been expected because the parking lot is mostly occupied by full-time employees. This information is relevant to companies or office buildings that intend to electrify their employees’ fleet. It can be used during the planning stage of the parking lot to estimate investment costs, charging infrastructure needed on site, electrical grid components, and power and energy contracts.

Given the fact that Cluster 1 is the most likely to occur, its characteristics on a daily basis are further investigated. Fig. 9 shows statistics of the daily utilization of the parking lot, i.e., the expected number of charging sessions and the energy demand per session for Sub-clusters 1–3. Note that the parking lot is particularly busy on Tuesdays and Thursdays with around 8, 15, and 10 charging sessions on average for Sub-clusters 1–3, respectively. On Fridays, the parking lot is barely busy (Fig. 9(a)). Furthermore, the energy demand of each sub-cluster follows a similar behavior throughout the week. Note that in Fig. 9(b) the median is around the middle of the boxes, and the whiskers are almost equal on both sides of the boxes, indicating a symmetric distribution or potentially normal distribution for the daily energy demand.

The daily utilization of the sub-clusters with a higher probability of occurrence can be used for operational purposes at the parking lot, such as predicting the day-ahead energy requirements, quantifying the EV flexibility, and designing EV charging strategies at office buildings.

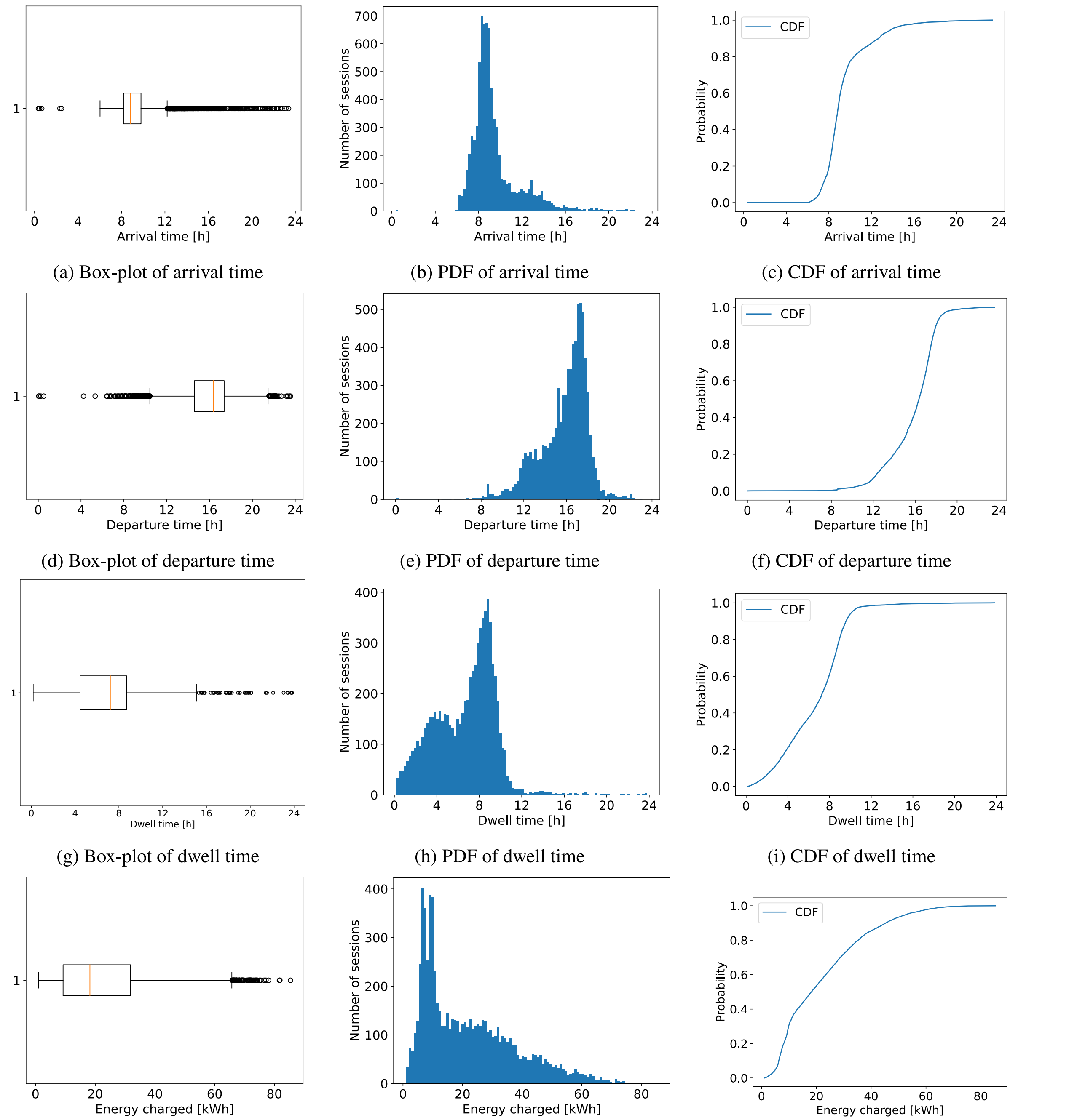
3. EV charging at office buildings

This section describes the methods used to simulate EV charging at office buildings and to validate the performance of offline plannings dependent on the degrees of available information. First, a description of the simulation environment and model implementation is provided (Section 3.1), followed by the description of the performance metrics proposed to validate the added value of historical information on EV charging (Section 3.2).

3.1. Simulation environment and model implementation

EVs can be charged under different strategies according to the interests of the entity responsible for the charging process (e.g., an EV aggregator or a grid operator). The deployment of such strategies depends on several factors, e.g., EV technology, charging infrastructure, and controllability of systems on site. For instance, in the absence of an energy management system, EVs are usually charged as soon as they are plugged into the charger at a maximum power resulting from the nominal power of the charger and EV. This is commonly known in the literature as *uncontrolled* or *dumb* charging [43] and in this paper referred to as greedy charging. However, if an energy management system is present, smart charging strategies for EVs can be deployed for various objectives.

The smart charging strategy implemented in this paper is based on the profile-steering algorithm [44]. Profile steering is a generalized optimization technique that, based on a target profile, aims to minimize the difference between this target profile and a planning profile, using as a measure the ℓ_2-norm of the difference profile. In this work, a constant aggregated power profile is used as the target profile. However,



(a) Box-plot of arrival time
(b) PDF of arrival time
(c) CDF of arrival time
(d) Box-plot of departure time
(e) PDF of departure time
(f) CDF of departure time
(g) Box-plot of dwell time
(h) PDF of dwell time
(i) CDF of dwell time
(j) Box-plot of energy demand
(k) PDF of energy demand
(l) CDF of energy demand

Fig. 3. Summary statistics of the data set.

Table 2
Clusters for charging behavior at the office building.

Cluster	Description	Sub-cluster	Mean arrival time [h]	Mean dwell time [h]	Mean energy [kWh]	Mean departure time [h]	Probability
1	Employees - Long stays (72%)	1 - High energy	9	7	47,16	16	16%
		2 - Medium energy	9	7	21,80	16	40%
		3 - Low energy	8	8	8,01	17	17%
2	Employees/visitors - Short stays (18%)	4 - Low energy	10	4	8,38	14	10%
		5 - High energy	12	4	22,16	16	8%
3	Visitors - Very short stays (8%)	6 -Low energy	12	1	4,55	13	2%
		7 - Medium energy	12	2	24,42	14	6%
4	Overnight users (1%)	8 - High energy	12	12	57,89	13	0%
		9 - High energy	19	16	31,22	10	1%

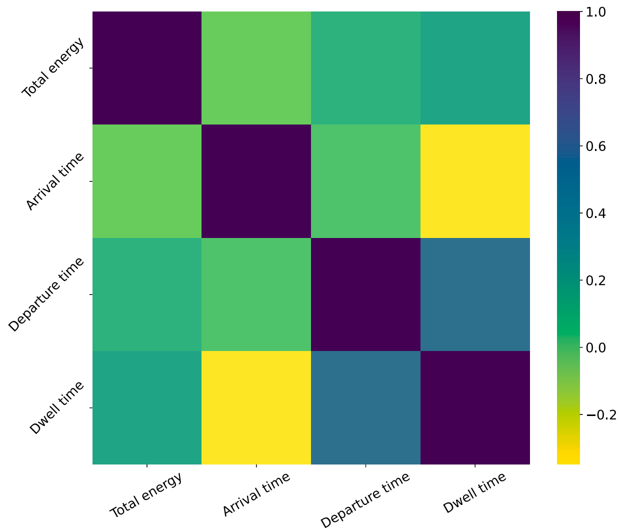


Fig. 4. Global correlation among the parameters.

note that it is straightforward to incorporate e.g., the base loads or grid capacities into the target profile. For smart charging in office buildings, the profile steering algorithm creates a power charging profile for EVs parked in the parking lot, given a set of input parameters related to the characteristics and preferences of each EV user (e.g., arrival time, energy required, etc.).

The profile steering algorithm is embedded within DEMKit, a *Decentralized Energy Management toolKit* that provides a cyber–physical systems-oriented framework to do research on smart and sustainable energy solutions. DEMKit is an open-source software [45] built with abstract device models and optimization algorithms that can be used as a platform to test innovative solutions through computational or even hardware-in-the-loop simulations [46]. All simulation results presented in this paper are obtained using DEMKit.

The EV charging model used in DEMKit includes the constraints related to EV charging such as fulfillment of energy required and the nominal charging power of the chargers [47]. Furthermore, DEMKit allows for making an offline charging planning (day-ahead) based on historical charging data of the parking lot and simulating the real-time operation of the parking lot with real information on EV availability and energy demand. Here, EV availability refers to the interval between arrival and departure time. Historical information is used to determine (individual) averages and percentiles of the various data features of the EVs (e.g., dwell time and energy requirement), which are later used as simulation input. Moreover, real-time operation profiles follow the offline planning as closely as possible, given real EV availability and energy charging requirements.

In the following, an illustrative example of the implemented simulations is given (Fig. 10). Assume there is prior knowledge of which EVs are going to charge on a particular day along with their (individual) estimated availability and average energy requirement. Then, the offline planning defines a charging profile per EV (blue lines Fig. 10) such that the aggregated power profile is as flat as possible. During the real-time operation of the parking lot, EVs may arrive or depart at different times than estimated. For instance, in Fig. 10(a) an offline planning (blue line) is made based on the estimated availability of the EV (blue area). However, during real-time operation, the EV arrives and departs at times different from the estimated ones (orange area). Therefore, the realization (orange dashed line) follows the offline planning only where possible. Even if the EV arrives before or departs after the original planning horizon, the planning does not update. If the realization is disjoint from the estimated availability of the EV, no charging takes place (Fig. 10(b)). Note that the charging process takes place during the real availability of the EV, but always follows the schedule from the offline planning (Fig. 10(c)). On the other hand, the charging process stops prematurely once the EV meets its energy requirement (Fig. 10(d)). In that case, the amount of energy scheduled in the offline planning for that particular EV was overestimated. This work does not take re-planning into account to instead study the value of historical information for the offline planning.

3.2. Performance metrics

The performance of the offline EV charging plannings for the operation of the parking lot under different degrees of available information is validated through a set of quality metrics measuring satisfaction from the user perspective based on energy not served and from the grid perspective based on peak power. In the following, the corresponding notation and definitions are introduced.

3.2.1. Energy not served

The simulated EV population is given as $EV = \{1 \dots n\}$, where n is the total number of EVs, and E_i denotes the energy supplied to EV $i \in EV$. For the validation of the performance of the offline EV charging planning under different degrees of available information, the set of superindices $\{0,\ plan,\ real\}$ is introduced, referring to the outputs from a baseline case (0), offline planning (plan), and real-time operation (real). Following that logic, E_i^0, E_i^{plan}, and E_i^{real} are the energy supplied to EV i with respect to the baseline case, offline planning, and realization. It is important to mention that the performance metrics use a baseline case considered in this paper to be greedy charging, i.e., the energy supplied E_i^0 is achieved by greedily charging the EVs upon arrival.

Three performance metrics for the individual absolute energy not served are defined. One is the energy not served of the offline planning relative to the greedy baseline given by (1). Eq. (2) calculates the energy not served of the realization relative to the greedy baseline, and (3) is the energy not served in the real-time operation relative to the offline planning.

$$ENS_i^{plan} := \max(0, E_i^0 - E_i^{plan}) \tag{1}$$

$$ENS_i^{real} := \max(0, E_i^0 - E_i^{real}) \tag{2}$$

$$ENS_i^{mismatch} := \max(0, E_i^{plan} - E_i^{real}). \tag{3}$$

Based on these individual performance metrics, average energy not served over the total EV population is given by:

$$ENS^x := \frac{\sum_{i=1}^n ENS_i^x}{n} \qquad \forall x \in \{plan, real, mismatch\}. \tag{4}$$

The above measures are absolute values. As within an EV population, significant variations exist in the energy demand of individual EVs, a relative counterpart for energy not served (denoted with lowercase letters) is defined:

$$ens_i^x := \frac{\max(0, E_i^0 - E_i^x)}{E_i^0} \qquad \forall x \in \{plan, real\}$$

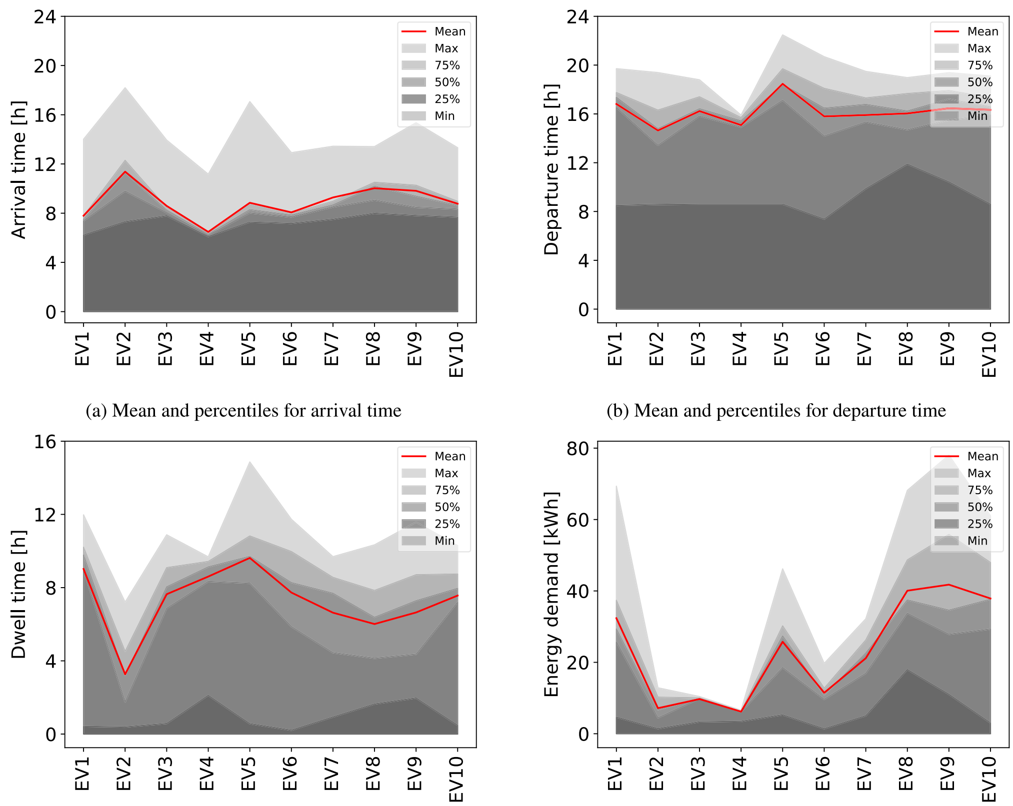
$$ens_i^{mismatch} := \frac{\max(0, E_i^{plan} - E_i^{real})}{E_i^{plan}}.$$

The averages are defined following the logic of their absolute counterparts (4), with instead of absolute energy not served, the relative values. Next to averages, one may also consider metrics to express the maximum energy not served:

$$ENS_{\max}^x := \max\{ENS_i^x | i = 1, \dots, n\} \qquad \forall x \in \{plan, real, mismatch\}$$

$$ens_{\max}^x := \max\{ens_i^x | i = 1, \dots, n\} \qquad \forall x \in \{plan, real, mismatch\}.$$

Note that the above metrics focus on the supply and service quality from the user perspective.



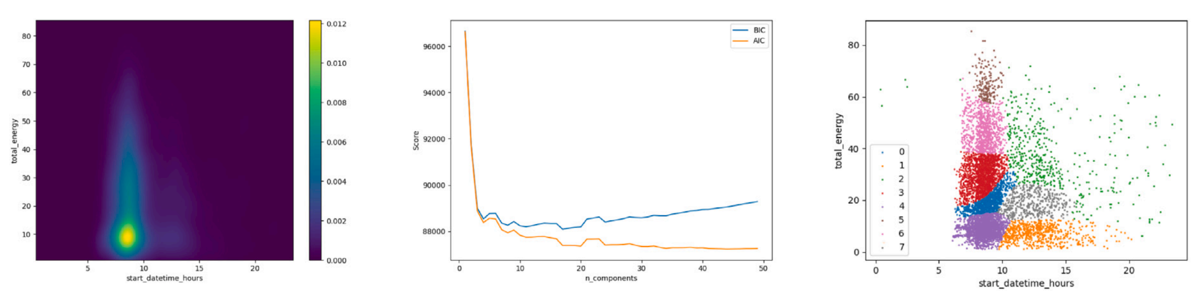
(a) Mean and percentiles for arrival time

(b) Mean and percentiles for departure time

(c) Mean and percentiles for dwell time

(d) Mean and percentiles for energy demand

Fig. 5. Summary statistics for 10 particular EVs.

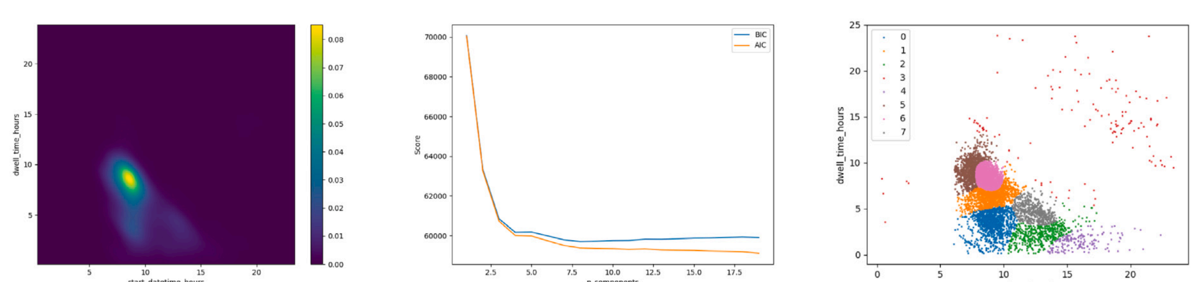


(a) Data distribution

(b) BIC and AIC metrics

(c) Cluster identification

Fig. 6. Clusters by arrival time and energy demand.

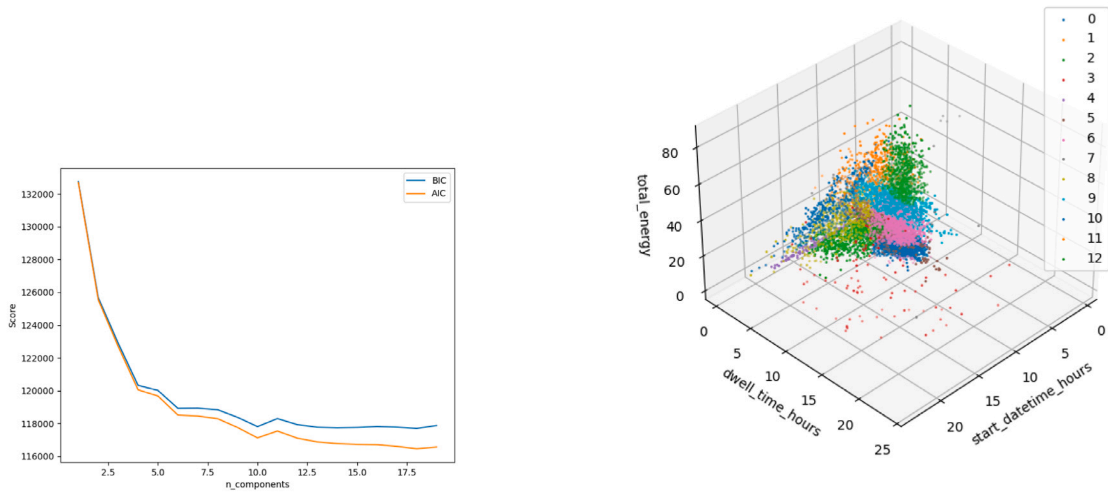


(a) Data distribution

(b) BIC and AIC metrics

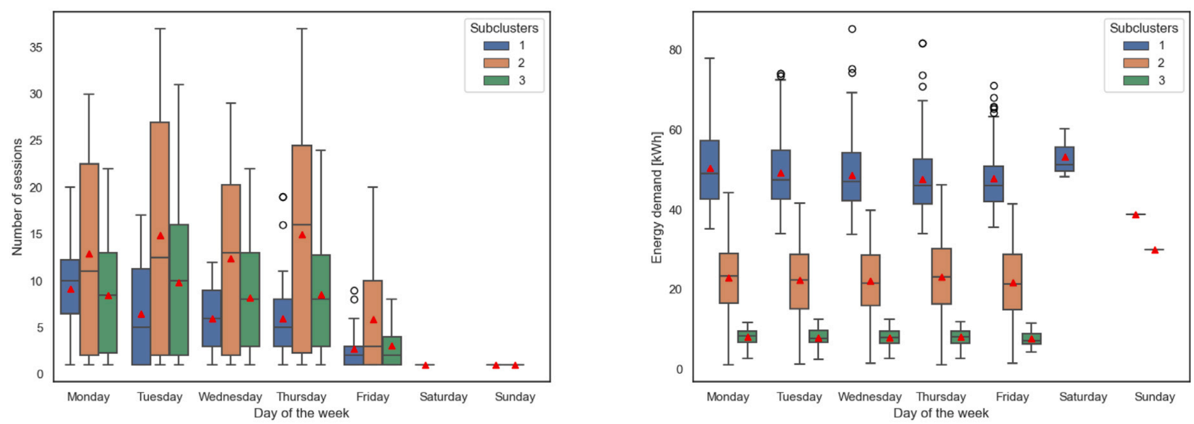
(c) Cluster identification

Fig. 7. Clusters by arrival time and dwell time.



(a) BIC and AIC metrics (b) Cluster identification

Fig. 8. 3D clusters by arrival time, dwell time and energy charged.



(a) Daily amount of charging sessions (b) Daily amount of energy demand

Fig. 9. Daily utilization of the parking lot for Cluster 1, Sub-clusters 1, 2, and 3.

3.2.2. Maximum energy and power peaks

Given the in-practice limited capacity of Dutch grid connections, two types of metrics are defined that focus on the aggregated impact on the local electricity grid: The first regards peak power, and the second considers total energy served. For this, baseline, offline planning, and real-time operation are expressed by power profiles of individual EVs i over a discrete time horizon $\mathcal{T} := \{0, \dots, T\}$ as $P_i^0(t)$, $P_i^{plan}(t)$ and $P_i^{real}(t)$, $t \in \mathcal{T}$. The aggregated power profiles for each $t \in \mathcal{T}$ are:

$$P^x(t) := \sum_{i=1}^{n} P_i^x(t) \qquad \forall x \in \{0, plan, real\}.$$

Finally, the peak power of a power profile $P^x(t)$ is denoted as

$$P_{max}^x := \max\{P^x(t) | t \in \mathcal{T}\} \qquad \forall x \in \{0, plan, real\}$$

and the total energy served per EV i can then be expressed as :

$$E_i^x := \sum_{t \in \mathcal{T}} P_i^x(t) \cdot \Delta_t \qquad \forall x \in \{0, plan, real\}$$

where Δ_t is the size of time step $t \in \mathcal{T}$. When summed over all EVs, these performance metrics provide information on the global energy consumption of the parking lot.

Depending on the specific needs and goals of the EV parking lot, additional metrics such as self-sufficiency or user fairness can be incorporated to provide a more comprehensive analysis of sustainability goals or equitable distribution of charging resources among users. However, such analysis is beyond the scope of this work.

4. Simulations and results

4.1. Simulation setup

The performance of offline EV charging plannings under different degrees of available information is evaluated based on data collected between January 1st, 2020, and August 30th, 2022 (*training data*). All the individual average arrival times, dwell times, and energy charged for each EV of the training period are stored as input files to the simulation environment in DEMKit. Based on this data, an offline day-ahead planning for one day, namely August 31st, 2022 is generated. This implies that the planning horizon is one complete day, discretized in time steps of 15 min. On August 31st 2022, 65 EVs were registered for charging.

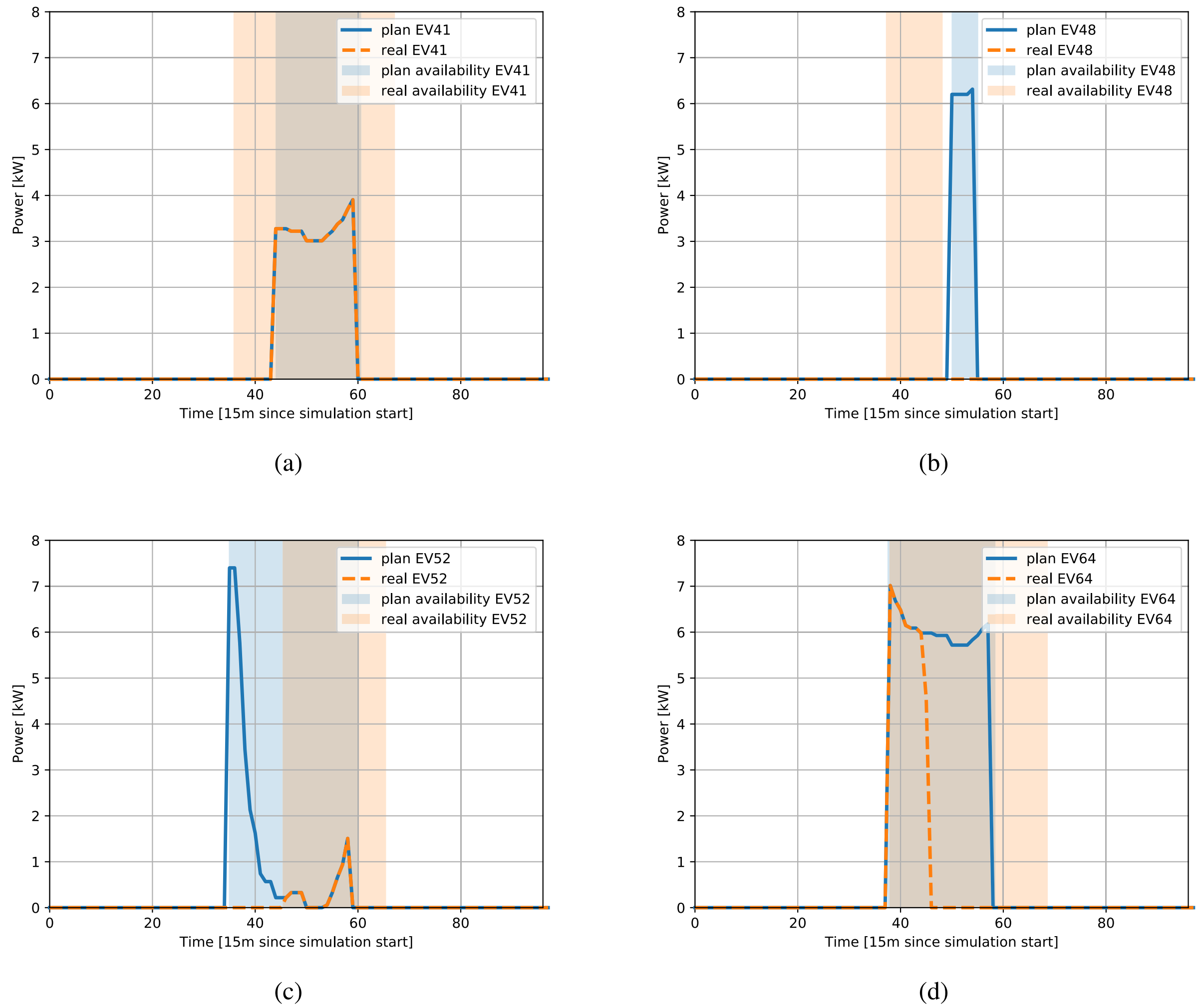


Fig. 10. Illustrative example of the simulations implemented using DEMKit.

4.2. Case definition

One of the main goals is to assess the added value of historical information on planning the EV charging of recurring users. To achieve this goal, several cases with varying degrees of information availability are defined. Table 3 provides a comprehensive overview of the information available per case. In the 'Real information' column, the entries for *arrival*, *dwell* and *energy* correspond to the information collected at the parking lot. On the other hand, the 'Historical information' displays availability of the *average arrival*, *average dwell*, and *average energy*, which are the estimated values per user based on historical data, and used in the offline planning.

The main goal of the charging system is to provide EVs with energy to its best ability based on the available information. Note that to achieve this goal, in current practice mainly greedy charging (or uncontrolled) is used. However, also other charging strategies may be used which utilize information on energy demand and power, as well as the availability of each EV (dwell time) if such data is available. In cases where insufficient data is available, greedy charging is left to be the only viable option.

In total, six cases are defined and detailed below. All cases assume knowledge of which EVs will arrive on the simulated day. For some cases only global knowledge of the historical average energy requirement (21.779 kWh) is available and no individual historical data on the energy requirement is given.

- Case 0 is the base case, corresponding to business-as-usual operation. It assumes the total absence of historical data, which makes it impossible to make an offline planning. This case is referred to as the greedy case since uncontrolled charging upon arrival is simulated.
- Case 1 assumes historical information on individual arrival times. The simulation uses the individual average arrival time as starting time of the charging, generating an offline planning where EVs charge at their maximum power upon arrival. Here, dwell times and energy requirements are unavailable for planning. Therefore, a static departure time of 17:00 is assumed for all EVs. Similarly, the energy requirement is set to the global average energy charged per session (21.779 kWh).
- Case 2 assumes historical information on individual arrival times and energy requirements. The offline planning for this case uses greedy charging starting at the average individual arrival time until either the average energy requirement is supplied (i.e., the EV stops the charging process prematurely), or until the default departure time (17:00).
- Case 3 assumes historical information on individual arrival and dwell times. In the offline planning, EVs greedily charge at most the global average energy requirement of 21.779 kWh within their estimated availability.
- Case 4 assumes historical information on arrival times, dwell times, and energy requirements. Since all the information is available, an offline planning is made using the profile steering approach.
- Case 5 assumes perfect (day-ahead) information on the realized session data and serves as a benchmark. The offline planning aims

Table 3
Overview of day-ahead information availability of individual EVs per case.

	Real information			Historical information		
	Arrival	Dwell	Energy	Average arrival	Average dwell	Average energy
Case 0 (C0)	✓	x	x	x	x	x
Case 1 (C1)	x	x	x	✓	x	x
Case 2 (C2)	x	x	x	✓	x	✓
Case 3 (C3)	x	x	x	✓	✓	x
Case 4 (C4)	x	x	x	✓	✓	✓
Case 5 (C5)	✓	✓	✓	x	x	x

to minimize the peak power consumption. This case leads to the flattest possible aggregated power profile that provides EVs with their full energy requirement. Additionally, since perfect information is considered, offline planning and real-time operation yield the same result.

All cases assume a homogeneous EV population with a maximum charging power of 7.4 kW. Next to Case 0, the assumptions made for Case 4 are the most likely to reflect a real-world parking lot. Therefore, for this case Section 4.4 further investigates the effect of different data inputs on offline planning and real-time operation of a parking lot via a parameter sweep.

4.3. Results

In this section, the main simulation results in terms of service quality to the user (energy not served) and power peaks in the local grid are presented and discussed per case. This combines both the customer- and the grid-centered points of view and allows for a proper assessment of the trade-off between the two objectives.

4.3.1. Analysis on service quality from the user perspective

First, the analysis focuses on the user perspective. Fig. 11 illustrates the energy not served metrics per case, showing the relative and absolute energy not served over all simulated EVs in the offline planning (ens^{plan}, ENS^{plan}), real-time operation (ens^{real}, ENS^{real}) and the mismatch between them ($ens^{mismatch}$, $ENS^{mismatch}$). The results are numerically summarized in Table 4.

As Case 0 acts as a baseline throughout this analysis, it by definition does not have energy not served. Table 4 shows that in Cases 1–4, on the other hand, there are EVs leaving without being charged at all, as indicated by the maximum relative energy not served of the realization (ens^{real}_{max}) being 100%. Even if the offline planning is perfectly followed, there are EVs leaving with 61.9% or 44.4% energy not served, relative to the baseline (ens^{plan}_{max}, Table 4). For Case 2, the control policy is greedy charging upon arrival until the generic 17:00 departure time, or until the estimated energy has been charged. The latter parameter is what makes Case 1 and 2 different, resulting in a lower value for ens^{plan}_{max} in Case 2. This demonstrates the added value of having historical information on the individual average energy requirement in the offline planning.

The difference between Cases 1 and 3 lies in the available information on average dwell time. Instead of a static dwell time, Case 3 considers historical averages. This results in slight differences in the service performance metric for the offline planning (ens^{plan}, Table 4), without a significant improvement in the real-time operation's energy not served (ENS^{real}). Therefore, having information about average individual dwell times does not add significant value to the performance of the offline planning and real-time operation in terms of energy not served. In both cases, EVs are planned to charge the global average energy which explains the similar results. Fig. 11(f) depicts the absolute energy not served in the real-time operation relative to the offline planning ($ENS^{mismatch}$), i.e., how much of the energy scheduled for an EV in the offline planning was not served during the realization, due to mismatches between the estimated availability and the realized availability. The assumption of EVs charging at most the global average energy in Cases 1 and 3 is reflected in this figure by the maximum $ENS^{mismatch}$ values (blue line and orange dashed line), which become stable at the predefined global average 21 kWh. Case 4 assumes historical information on individual arrival times, dwell times, and energy requirements. Table 4 shows that the average absolute energy not supplied (ENS^{real}), in this case, is limited to less than 4.5 kWh, and ENS^{real}_{max} is up to 19.7 kWh. In relative terms, on average Case 4 has 24.8% energy not served in the real-time operation (ens^{real}, Table 4), or equivalently EVs are charged with 75.2% of their charging requirement. There are still EVs that are not charged at all (100% ens^{real}_{max}, Table 4) and that according to the offline planning should have received at least half their charge (44.4% ens^{plan}_{max}, Table 4).

4.3.2. Analysis on power peaks from the local grid perspective

Next, the results are discussed from a local grid-perspective. It is important to note that at the time of data collection, given the robust physical infrastructure in Utrecht, the local electricity grid had sufficient power capacity to meet all energy requirements, even under greedy charging. However, when scaling-up, the compliance with the (contracted) capacity inevitably becomes of interest.

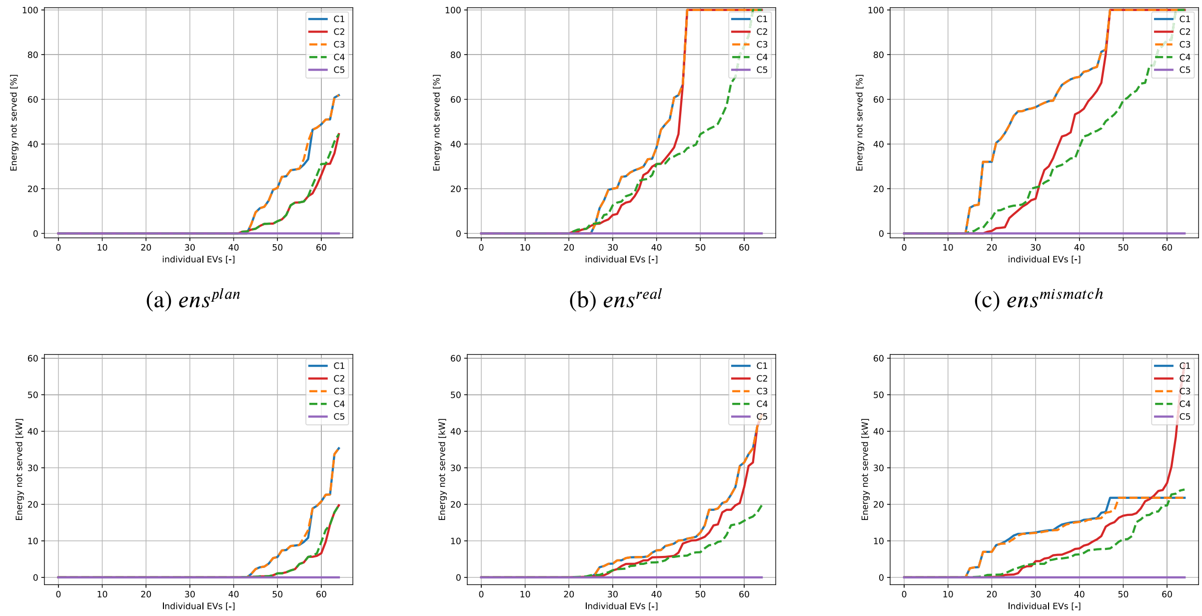
An overview of the results is given in Fig. 12 which depicts aggregated power profiles from offline planning and real-time operation per case. Table 5 numerically specifies maximum power peaks per case for the offline planning and real-time operation. There, the power peaks relative to the power peak observed in Case 0 are specified as ($P^{x}_{max}/P^{0}_{max}, x \in \{plan, real\}$).

Results for our baseline (Case 0) show a power peak of 297.6 kW (P^{real}_{max}, Table 5). For Case 1, where EVs are planned to charge the global average energy at maximum power and are expected to depart at 17:00, a big mismatch between the power peaks of the planning and realization can be observed (Table 5). The offline planning reserves almost twice as much energy as is ultimately used for EV charging (Fig. 12(b), area between blue and orange curves). In a market context, this would have economic implications for the parking lot operator overestimating the energy to purchase in the day-ahead market.

When comparing Case 1 and 2 one can observe that having knowledge of the average energy requirement (Case 2) also results in an improvement in the power peak (Table 5). The offline peak in Case 2 is approximately 22% less than in Case 1 (307.9 kWh and 397.9 kWh respectively), demonstrating the added value of historical information of the individual average energy requirement for the offline planning.

For Case 3, it is remarkable how the power peaks of both offline planning and real-time operation match those of Case 1 (P^{real}_{max} and P^{plan}_{max}, Table 5). That is because in both cases, EVs are planned to charge the global average energy. This result shows that having historical information on the individual average dwell time in the offline planning has little impact on local power peaks.

Case 4, the most realistic in terms of available historical data, shows power peaks almost halved compared to the power peak observed in the greedy baseline case for the offline planning and real-time operation ($P^{real}_{max}/P^{0}_{max}$ = 52% and $P^{plan}_{max}/P^{0}_{max}$ = 48.6%, Table 5). These results demonstrate the added value of data availability, since significant improvements in terms of power peaks can be achieved (at the expense of energy not served, see Section 4.3.1).



(a) ens^{plan} (b) ens^{real} (c) $ens^{mismatch}$

(d) ENS^{plan} (e) ENS^{real} (f) $ENS^{mismatch}$

Fig. 11. Energy not served performance metrics per case in load duration curve formats.

Table 4
Energy not served metrics.

	Real-time operation				Offline planning			
	[a] ENS^{real} [kWh]	ENS^{real}_{max} [kWh]	[a] ens^{real} [%]	ens^{real}_{max} [%]	[a] ENS^{plan} [kWh]	ENS^{plan}_{max} [kWh]	[a] ens^{plan} [%]	ens^{plan}_{max} [%]
Case 0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Case 1	8.4	44.5	38.4	100.0	4.0	35.3	10.1	61.9
Case 2	6.8	44.5	35.2	100.0	1.6	19.7	4.9	44.4
Case 3	8.4	44.5	38.4	100.0	4.0	35.3	10.3	61.9
Case 4	4.4	19.7	24.8	100.0	1.7	19.7	5.3	44.4
Case 5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

[a] Average values over the EV population.

Table 5
Grid-perspective metrics.

	Real-time operation		Offline planning	
	P^{real}_{max} [kW]	$\frac{P^{real}_{max}}{P^{0}_{max}}$ [%]	P^{plan}_{max} [kW]	$\frac{P^{plan}_{max}}{P^{0}_{max}}$ [%]
Case 0	297.6	100.0	297.6	100.0
Case 1	236.8	79.6	397.9	133.7
Case 2	236.1	79.3	307.9	103.5
Case 3	236.8	79.6	397.9	133.7
Case 4	144.5	48.6	154.7	52.0
Case 5	122.8	41.3	122.8	41.3

Lastly, results for Case 5 show a power peak reduction of 58.7% ($P^{real}_{max}/P^{0}_{max} = 41.3\%$, Table 5).

Overall, planning EV charging with only partial information available resulted in a gross overestimation of the aggregated energy required in the parking lot. Furthermore, a trade-off between energy not served and peak power was observed, with an increased impact under less information availability. Furthermore, comparing results between Cases 0 and 4 demonstrates the added value of data availability. Although energy not served is observed in offline planning and in real-time operation, significant improvements in terms of power peaks are achieved.

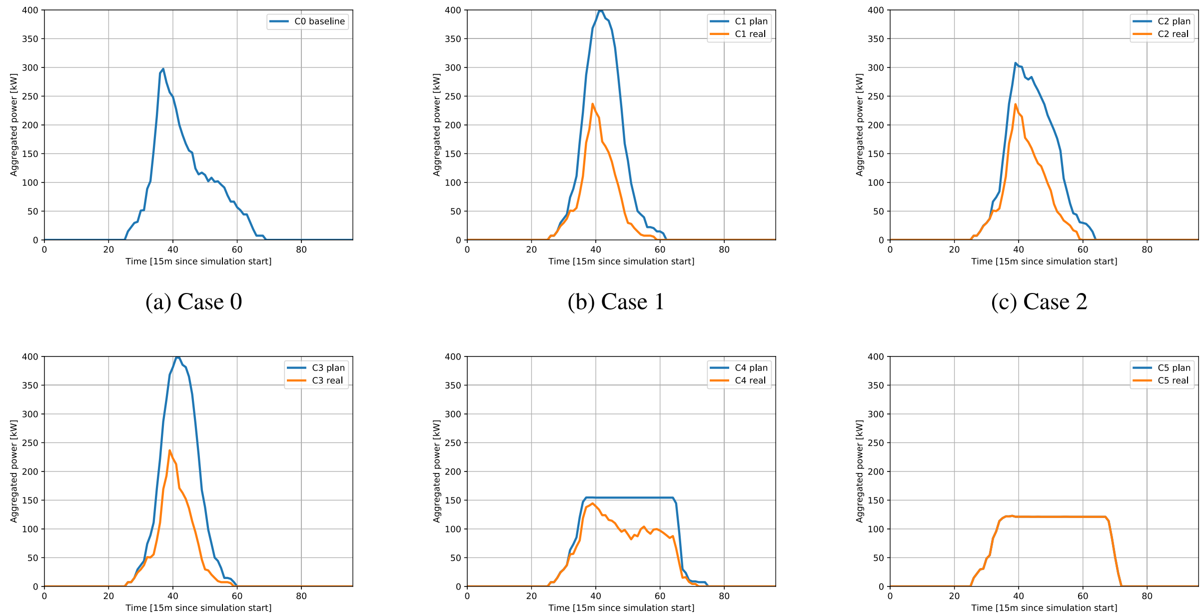
4.4. Parameter sweep analysis

This section explores the effect of considering different degrees of robustness (percentiles) for the arrival time, dwell time, and energy required for Case 4. Per individual user, instead of using mean energy demand as an estimation of the energy requirement, a parameter sweep over the percentiles is done. Next to the energy parameter, the sweep is also done over the time domain parameters. For this, the xth-percentile is defined to be the xth-percentile of the arrival time and the $(100-x)$th-percentile of the dwell time. Note that arrival and dwell time are not independent variables. However, the lower the percentile, the more conservative is the resulting interval and the higher the chance of an EV being available within that interval.

The results of the parameter sweep are shown in Fig. 13. From the sweep results one can see that in the current setup, there is always at least one EV that does not charge any energy in the realization. Given that the red dot in the graph represents the result of the mean-value for Case 4, the results clearly show that improvements in terms of power peaks and energy not served can be achieved by carefully calibrating the input parameters.

5. Discussion

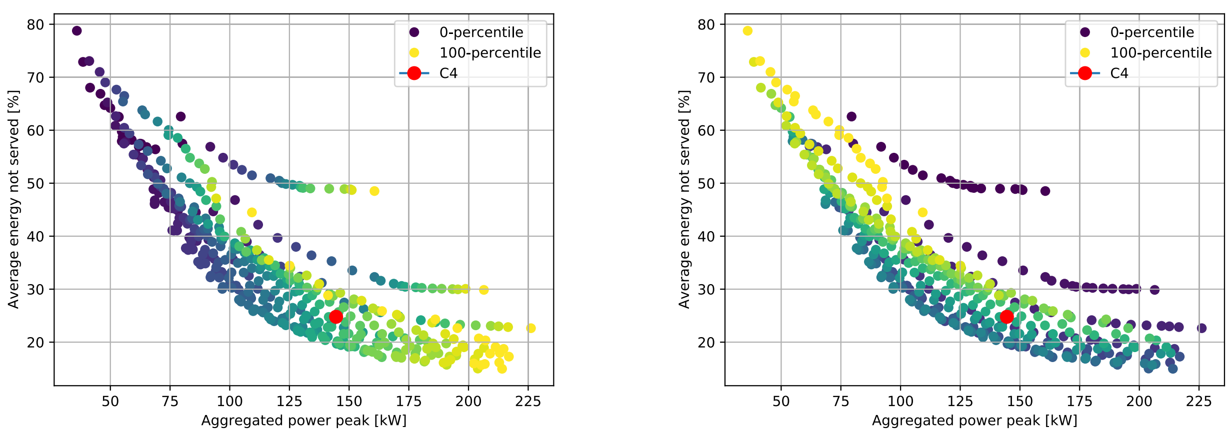
The results show a significant power peak reduction potential when utilizing historical data and strictly enforcing an offline planning for EV charging at an office building parking lot at the expense of energy not served. That is expected because in these simulations a "replanning"



(a) Case 0　(b) Case 1　(c) Case 2

(d) Case 3　(e) Case 4　(f) Case 5

Fig. 12. Aggregated power profiles for planning and realization.



(a) Color scale corresponds to energy percentile.　(b) Color scale corresponds to time percentile.

Fig. 13. Realized sweep results for Case 4: plot P_{max}^{real} against ens^{real}.

stage is not considered. This was intentionally done to demonstrate how accurate offline plannings are under different degrees of available information when compared to the real-time operation of the parking lot.

Nevertheless, it seems interesting to investigate the impact of real-time "replanning" algorithms on energy not served and power peaks under different degrees of available information. Furthermore, instead of assuming perfect knowledge of the number of EVs that will arrive, it would be interesting to use information from the cluster analysis to estimate the number of EVs (per cluster) that will charge that day.

The achieved results indicate that the utilization of historical information for EV charging has great potential. The remainder of the section will discuss the approaches strong and week points.

Among the strong points of the utilization of historical information, the most prominent is information availability. As discussed in Section 1.1, effective smart charging methods require input. Hereby, historical information is relatively easy to register and acquire compared to direct user input. Furthermore, for the presented office building use case, the population is relatively stable and homogeneous. Therefore, it should be feasible to analyze charging behavior on the individual level.

On the other hand, there are some weaknesses to consider. Firstly, the approach does not necessarily translate well to use cases with less stable and more heterogeneous populations, e.g., public charging stations. Furthermore, long dwell times in near-work parking lots are advantageous for smart charging methods operating under uncertainty, which likely has a positive impact on the simulation results.

Secondly, irregular behavior (e.g., leaving work early), or systemic changes in the charging behavior of individuals (e.g., reducing work hours) have to be taken into account. Especially when collecting individual charging data for a long period of time, changes in charging patterns are likely to occur.

Similarly, before introducing a smart charging method based on historical data, a period to collect an initial data set is needed. For first-time visitors, this prevails even for long-running systems. This can be overcome by analyzing the typical aggregated profile of all visitors on any day of the week and subsequently use this as planning input.

Next to that, from the moment smart charging is introduced, the smart charging method itself interferes with the data set. That is the case since e.g., the amount of energy charged to an EV will be influenced by the method. The system, however, is not aware of whether or not the full energy requirement was met. The historical information is then not sufficient to evaluate the charging performance in practice. If not properly addressed, this can cause a feedback loop in future analyses and operation, iteratively reducing energy requirements.

6. Conclusion

Using greedy charging in office buildings leads to considerable power peaks due to synchronized arrival times. The presented results demonstrate that a reduction of more than 50% can be achieved using historical data and simple estimations per individual EV. Although energy not served is observed in offline planning and real-time operation, significant improvements in terms of power peaks can be achieved which demonstrates the added value of data availability. Results also demonstrated that having only partial historical data available is insufficient for effective offline planning and real-time operation. However, the performance of such plannings can be substantially improved if information on arrival times, departure times, and energy requirement is fully available.

Additionally, it was found that information on individual average energy charged has a higher added value than information on average dwell time in terms of energy not served and power peaks in both offline planning and real-time operation of office building parking lots.

7. Future work

The work presented here indicates a huge potential for office building parking lots as EV charging hot spots. However, further research is necessary. In the presented simulations, knowledge of which EVs will be present the next day is assumed. Instead, the clusters defined in Section 2.4 may be used to predict the EV population of the next day and use it as input for the offline planning. An online charging strategy can then use the resulting profile as a base for real-time operation. On the other hand, the clusters can be used to build stochastic models for smart charging of EVs using a scenario-based approach.

Furthermore, the method used to estimate the offline planning has to be more robust to behavior change. Data collection is ongoing and will include changes in charging prices, as well as individual behavior changes. Moreover, surveys among the EV-driving employees frequenting the parking lot will provide additional data on e.g., EV models, battery capacity and individual user preferences.

CRediT authorship contribution statement

Leoni Winschermann: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Visualization. **Nataly Bañol Arias:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Visualization. **Gerwin Hoogsteen:** Conceptualization, Writing – review & editing. **Johann Hurink:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgment

This research is conducted as part of the SmoothEMS met GridShield project (MOOI32005) subsidized by the Dutch ministries EZK and BZK.

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