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Increasing hosting capacity of low-voltage distribution network using smart charging based on local and dynamic capacity limits

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ABSTRACT

While the Municipality of Amsterdam wants to expand the electric vehicle public charging infrastructure to reach carbon-neutral objectives, the Distribution System Operator cannot allow new charging stations where low-voltage transformers are reaching their maximum capacity. To solve this situation, a smart charging project called Flexpower is being tested in some districts. Charging power is limited during peak times to avoid grid congestion and, therefore, enable the expansion of charging infrastructure while deferring grid investments. This work simulates the implementation of the Flexpower strategy with high penetration of electric vehicles, considering dynamic and local power limits, to assess the impact on both the satisfaction of electric vehicle users and the business model of the Charging Point Operator. A stochastic approach, based on Gaussian Mixture Models, has been used to model different profiles of electric vehicle users using data from the Amsterdam public electric vehicle charging infrastructure. Several key performance indicators have been defined to assess the impact of such charging limitations on the different stakeholders. The results show that, while Amsterdam's existing public charging infrastructure can host just twice the current electric vehicle demand, the application of Flexpower will enable the growth in charging stations without requiring grid upgrades. Even with 7 times more charging sessions, Flexpower could provide a power peak reduction of 57% while supplying 98% of the total energy required by electric vehicle users.

1. Introduction

Electric vehicles (EVs) are seen as an essential part of the energy transition towards a low-carbon system while reducing the number of local pollutants. Therefore, cities with strong clean air plans are at the forefront of the transition to electric mobility and they are investing in charging infrastructure to facilitate this transition. The adoption of EVs is directly related to the development of the public charging infrastructure [1], especially in dense urban areas where EV drivers require charging points at both home and workplace.

However, a city-scale deployment of a public EV charging infrastructure poses a chain of challenges for both the Distribution System Operators (DSO) — who have to ensure the quality of power supply — and the Municipalities — who want to expand the public charging infrastructure. The EV peak demand largely aligns with the demand from households, increased by the electrification of energy-intensive domestic activities such as space-heating (e.g. heat pumps) and cooking [2–6]. Consequently, this leads to larger daily demand peaks that may exceed the maximum capacity of certain low-voltage transformers, resulting in a bottleneck in the distribution system. To avoid this congestion scenario, the DSO should incur in costly investments to upgrade the congested transformers [5], which may not be performed in a short period of time. Deferring the upgrade would imply that no more charging stations could be installed downstream of the congested transformers, and the low-carbon objectives of cities and governments could be affected. Thus, since a grid upgrade is not expected in the short term, the only option to continue expanding the charging infrastructure is to apply a 'smart charging' strategy, reducing the reserved capacity for every charging station according to the grid availability.

However, the flexibility potential of EVs is significant since when using public charging stations, they are often connected (parked) for a time significantly longer than needed for charging. This happens overnight, during work time or when visiting the city [7], giving the potential to shift power demand over time without interfering with the charging needs of the EV user. Such smart charging strategies are widely discussed in the literature with different objectives — technical (e.g. load balancing or increasing PV usage) or financial (e.g. reducing energy cost) —, control architectures (centralized or distributed charging) and control algorithms (e.g. linear programming, quadratic

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programming, rule-based algorithms, etc.) [8]. Moreover, to a certain extent some smart charging pilots have already been tested in the field with public charging infrastructure [9,10] and private home charging points [11–13]. However, a city-scale smart charging deployment is still a challenge due to a combination of technical, economic and societal issues [14]. Especially in the public charging market at city-scale, the high penetration of EVs has to deal with a complex equilibrium among technical requirements of the DSO (congestion and peak avoidance, voltage control, etc.), the energy-intensive business model of the Charging Point Operator (CPO), the mobility and charging behaviour of EV users and the charging infrastructure deployment plans of cities and/or governments. Also, it is important to remark that, even though the real impact of Distributed Energy Resources (DER) like EVs appears in the low-voltage distribution level and this impact is diverse depending on the location and time, most of the literature does not consider these local grid constraints and mainly adopt a global perspective and refer to approaches linked to implicit flexibility strategies based on the electricity price [15–17], the impact of renewable production at transmission-level [17–20], national flexibility markets [12] or modelling user profiles at wide-scale [11,21,22]. Thus, despite the low degree of instrumentation of these infrastructures, low-voltage lines and transformers are the first assets that have to be protected from the volatility of DER. To solve this issue, it is crucial to promote decentralized smart charging programs based on local grid signals, like the Flexpower project [23] in Amsterdam, the Netherlands, which is described in more detail in Section 2.

Flexpower is a novel smart charging approach for future smart cities, where the CPO controls the power of public charging stations according to the capacity signals sent by the DSO. These capacity signals are local (low-voltage transformer level) and dynamic (15-minute resolution). Therefore, the aim of this work is to simulate and analyse the Flexpower impact given scenarios with high penetration of EV in the public charging infrastructure, taking into account the main interests, objectives and concerns of all stakeholders involved:

- Municipality: the objective of the city council is to expand the charging infrastructure to incentivize the citizens to buy EVs and reach their low-carbon city objectives. Their main concern is that the DSO could not host the expected charging infrastructure growth in the near future. Moreover, they do not want Flexpower to affect the quality of the charging service, controlling the EV load without noticeable changes by the user.
- Distribution System Operator (DSO): their objective is to ensure a high-quality power supply with a minimum cost, so managing power congestion to defer investments in infrastructure upgrades. Flexpower will allow them to avoid grid congestion while expanding the charging infrastructure.
- Charging Point Operator (CPO): their objective is to provide a good and reliable service to all EV users of the public charging infrastructure, supplying all energy requirements the users have. Flexpower could limit their benefits if EV charging is curtailed, but also could increase them if the charging infrastructure is expanded.
- EV users: their objective is to connect the vehicle when they need it and charge all the energy needed. Their main concern would be that Flexpower could limit their charge and affect their routes or plans.

This work wants to provide answers to these multiple concerns and offer more information to all stakeholders involved in the project. With this purpose, Section 2 gives first an introduction to the Flexpower project as a context for the study and the methodology proposed in Section 3. Following, Section 4 describes the calculations performed using real data from a trial at 124 public charging points to model the existing EV user profiles and uses these models to generalize the study across different locations in the city. The results from these calculations are analysed in Section 5 and, finally, Section 6 concludes the paper with the main outcomes from the analysis and the recommendations for the further development of the Flexpower project in the city of Amsterdam.

2. The context: Flexpower project in Amsterdam

The city of Amsterdam has been at the forefront of the transition to electric mobility since the installation of the first public charge point in 2009. By 2030 the city aims to only allow zero-emission mobility into the city with an estimated total of 254.000 passenger cars (100% electric) [24]. To accommodate electric mobility, the city has set out a plan to install a total of 82.000 charging points across the city by 2030 [25]. Of those, 18.000 should be publicly accessible. By November 2022, there are 6.000 charging points (i.e. 3000 charging stations) installed in public areas [26]. The majority of charging should be done at private (50.000) and semi-public locations (13.000). Significant growth in infrastructure is thus expected.

Every public charging station has a grid connection of 3 × 25 amperes, which means that, traditionally, every charging station had a technical capacity of 25 A. However, to allow the planned charging infrastructure expansion by the municipality and, at the same time, to avoid the congestion of low-voltage transformers, the reserved capacity for every charging station has to be reduced according to the grid availability. In that line, the Municipality of Amsterdam has been working on a smart charging project called Flexpower since the beginning of 2018. Initially, Flexpower was a pilot project within the EU Interreg project SEEV4City [27] and currently, the project is being further developed with high interest from all the partners involved in the project, including the DSO and the CPO.

In the first two iterations of the Flexpower project (i.e. Flexpower1 [28] and Flexpower2 [3]) a static load profile was deployed to 200 charging stations (each with two charging points) in Amsterdam. During the project, the physical grid connection was upgraded to 3 × 35 A to allow higher loads during periods with high PV solar generation. The aim was to allow more locally produced renewable energy to be charged. During peak hours (16:00–19:00) a lower load (max. 3 × 8 A per charging session) was allowed to prevent peak load. The results of the project showed that such a profile was partially effective. Allowing higher charging power during sunny days was hardly effective since, on one hand, only a very small portion of cars could charge faster than 3 × 16 A and, on the other hand, it required a considerable investment for the grid upgrade. A lower load during peak hours worked but resulted in a rebound demand peak when the charging signal profile allowed higher loads. The profile was applied in a similar manner each day (depending on the weather forecast) without information about the actual load on the local low-voltage transformer.

In the third phase of Flexpower project in 2022 (i.e. Flexpower3 [29, 30]), the power regulation of the charging station is done with a dynamic capacity signal for all charging stations under the same low-voltage transformer, middenspanningsruimte (MSR) in Dutch [31]. The current pilot consists in 62 public charging stations (124 charging sockets), under 9 different MSRs, with a maximum charging power of 11 kW per socket (3 × 16 A). The dynamic capacity signal is calculated by the DSO considering the nominal power capacity of every MSR and the forecasted demand of the other loads. The EV demand is controlled to avoid peaks in the aggregated power demand, while a minimum charging capacity is always guaranteed by the DSO. Then, according to this capacity signal, the CPO has to limit the output power of the EV charging stations installed downstream the corresponding MSR. Fig. 1 illustrates an example of this dynamic capacity signal established by the DSO during one day of September 2022.

Fig. 1 also shows two red dashed lines representing the minimum and maximum capacity limits, which are obtained according to Eqs. (1) and (2) respectively, and are given by the number of charging stations installed downstream the MSR and the values of $ReservedCapacity$ and $FirmCapacity$:

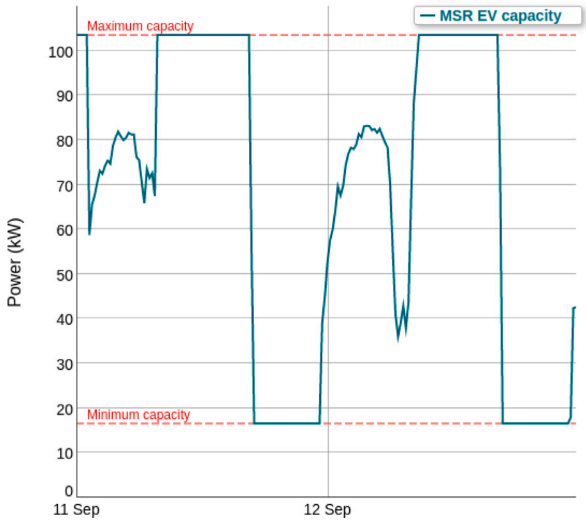

Fig. 1. MSR (low-voltage transformer) capacity sent by the DSO.

- *ReservedCapacity*: power capacity for the connection of every charging station in the power grid, which is currently of 25 amps/phase. When a new charging station is installed in a street, the DSO registers this new point of demand and assigns it to the corresponding MSR.

$$MaximumCapacity = nChargingStations \times ReservedCapacity \quad (1)$$

- *FirmCapacity*: guaranteed power capacity that will be provided to a charging station at any moment, which is currently of 4 amps/phase. This is a regulation measure to ensure a good charging service for all EV users even though the charging power is limited.

$$MinimumCapacity = nChargingStations \times FirmCapacity \quad (2)$$

Observe that the capacity limit in Fig. 1 is represented in power units to facilitate the understanding of the power system, despite the DSO defining it in amperes per phase (i.e. power current I). Thus, the limits obtained with Eqs. (1) and (2), as the results of multiplying the *ReservedCapacity* and the *FirmCapacity* by the number of charging stations (6 charging stations in the example from Fig. 1), are converted to power capacity considering an equilibrated three-phase low-voltage system using Eq. (3).

$$P_{III} = \sqrt{3} \times 400 \times I \quad (3)$$

The current *MaximumCapacity* of every MSR has been established with the current number of charging stations (See Table 1). These are the capacity limits that reduce the possibility of supplying extra EV demand without upgrading the grid infrastructure (i.e transformer, lines and protections). On the other hand, the *FirmCapacity* could be decreased to allow the charge of more users under the same MaximumCapacity. However, very low values of *FirmCapacity* could result in a higher amount of uncompleted sessions due to longer charging times. Thus, a relevant part of the calculations done in Section 4 assesses multiple values of *FirmCapacity* for every scenario. This allows for identifying which value ensures a good charging service to EV users and at the same time guarantees reliable demand profiles for the distribution grid.

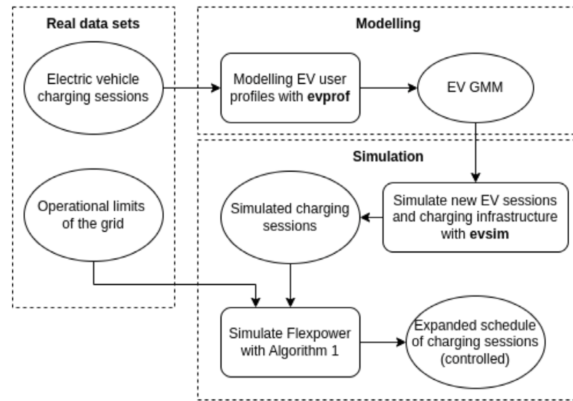

Fig. 2. Methodology block diagram.

Table 1
MaximumCapacity values for every MSR.

MSR	Charging stations	Max.capacity (A/phase)	Max. capacity (kW)
9020467	7	175	120.75
9006775	7	175	120.75
3023573	9	225	155.25
9015800	6	150	103.50
3023598	8	200	138.00
3016877	6	150	103.50
3002819	6	150	103.50
3002917	7	175	120.75
3006277	10	250	172.50

3. Materials and methods

This section details the data, algorithms, and methods used to analyse the impact of the Flexpower project in Amsterdam. A summary of the methodology is illustrated in Fig. 2.

3.1. Data sets

The following real data sets used in this work were provided by the University of Applied Sciences of Amsterdam (Hogeschool van Amsterdam) in the scope of a research collaboration. The EV charging data sets are not public but available under request through evdata.nl [32].

3.1.1. Electric vehicle charging sessions

A real data set of electric vehicle charging sessions from the city of Amsterdam was used in this study to create EV stochastic models and to obtain the current charging picture of the city. This data set consists of more than 2.6 million sessions during 2020 and 2021, every session being defined by connection times, energy charged, type of connection (1 × 16 A, 2 × 16 A or 3 × 16 A), charging point ID and MSR ID.

3.1.2. Operational limits of the grid

Another real data set used in this work is the grid capacity limits that the DSO sends to the CPO in the scope of the Flexpower project, as explained in the Introduction section. The real capacity limits (in amperes per phase) for every one of the 9 MSR participating in the project during the month of September 2022 were provided in a resolution of 15 min.

Moreover, the number of charging stations supplied by every MSR was also provided. Therefore, the *MaximumCapacity* for every MSR is shown in Table 1, considering a *ReservedCapacity* of 25 amperes.

3.2. Models of electric vehicle charging sessions

The simplified demand profile of a charging session can be characterized by the connection times, the charging power and the energy required [33]. The duration of connections highly depends on the user behaviour (e.g. daily activities or work timetable), whereas the charging power depends on the type of connection (single-phase, two-phase or three-phase) and the maximum current per phase that either the EV or the charging station permits (usually 16 A). Finally, the energy that the vehicle can charge depends on both the user behaviour (i.e. the distance travelled, level of the battery), the size of the EV battery and the charging power (i.e. how fast it can charge the energy requirements). Thus, while the charging power is a simulation parameter that can be defined according to the charging infrastructure of a specific use case (e.g. 20% of sessions charging at 3.7 kW and 80% at 7.4 kW), the EV user behaviour in terms of connection patterns and energy requirement must be defined by stochastic models that capture the uncertainty associated with the EV demand at issue [34].

Therefore, stochastic models are built from the real Amsterdam data set described in Section 3.1.1 to characterize EV user profiles, understanding a “user profile” as a pattern in the connection times of charging sessions. These stochastic models are then used to simulate multiple levels of EV penetration in the public charging infrastructure of Amsterdam. The modelling methodology proposed can be summarized with the following steps:

1. Clustering of charging sessions: Resulting clusters will represent generic user profiles (i.e. connection patterns that reflect different user behaviours)
2. Building the connection models for every user profile: Associating every profile with a connection start time and a duration.
3. Building the energy models for every user profile and different charging powers.

Below, this section describes in more detail the methods used to cluster and model user profiles using a real data set of EV charging sessions. It is worth mentioning that the methodology has been wrapped into an open-source R package, called “evprof”, for free use in any other use case where charging session data is available [35].

3.2.1. Clustering EV sessions into user profiles

In the first step, a Gaussian Mixture Models (GMM) clustering is applied to the data set of EV charging sessions. Gaussian Mixture Models is a model-based clustering technique that groups data points into Gaussian distributions. The clustering methodology is widely explained in previous works, first in [36] and later improved in [37]. In this application, two variables are used to cluster sessions using a bivariate GMM: connection start hour and duration (connection hours).

As raised in [37], model-based algorithms are sensitive to outliers so first, the full data set is divided into smaller sets with similar density levels and taking into account the different time cycles where the EV users have different behaviour (day of the week, season, etc.). Then, every sub-set is cleaned after detecting the outliers with the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) method. Since the outlying sessions are not part of the main connection pattern during peak hours, they do not suppose a relevant power demand for grid congestion analysis. After cleaning the outliers, every cleaned sub-set is evaluated with the Bayesian Information Criterion (BIC) to define the optimal number of clusters to describe the data points and avoid overfitting. The BIC indicator is the value of the maximized log-likelihood with a penalty on the number of parameters in the model, so it allows a comparison of models with different numbers of clusters. This comparison is done in a plot visualization using the evprof R package [35]. Once the number of clusters is defined, the GMM clustering method is applied to every subset to obtain the bivariate clusters. Finally, every cluster is labelled with a user profile name, corresponding to informative behaviours in terms of connection start time and duration. Thus, for example, a cluster with an average start tie at 9:00 and an average duration of 8 h is tagged as “Worktime”. A single user profile can have multiple clusters assigned to it. Some clusters may represent a very specific behaviour, but others could have a high variability that does not allow a clear identification of a user profile.

3.2.2. Modelling EV user profiles

This work proposes to model the EV charging sessions in terms of connection times and energy demand since these variables are defined by the behaviour of the EV users. EV user behaviour is interpreted in multiple ways in current literature. For example in [38] the EV user behaviour is modelled in terms of importance given by the user to aspects such as charging price, comfort or the battery state of charge. However, modelling the EV demand at this high-detail level requires EV user information (e.g. vehicle ID, state of charge, distance driven, etc.) that was not available in the data set of this work. Thus, the stochastic modelling methodology used in this work for city-scale simulations makes use of basic charging variables like connection times, energy and power to model generic EV user profiles (i.e. connection patterns) that will have a specific presence depending on the district of the city or the area under study.

The GMM clustering method raised in Section 3.2.1, based on the connection start time and the connection duration, is a parametric method that allows classifying EV charging sessions into clusters at the same time that provides a centre of each model and a measure of dispersion. Therefore, the models of these connection variables for a specific user profile are built as an additive combination of the multiple bivariate Gaussian distributions (i.e. clusters) associated with that user profile. These connection GMM are defined by the mixture weight (%), the means vector (μ) and a covariance matrix (Σ). The connection GMM of the current study case are described in Appendix B.

On the other hand, the energy models are not part of the clustering process and have to be built afterwards. Previous work from the authors [39] presented a methodology to build GMM of a single variable, i.e. the energy charged per charging session, for every user profile. However, in the case study of the current paper, the research showed that the energy charged in every session not only depends on the user profile but also on the charging power (see Section 4.1). New EV models tend to have larger batteries but also charge at higher rates, so the higher the charging power, the larger the energy demand. Thus, every user profile has been associated with several energy models corresponding to the multiple charging rates. In particular, in the data set used in this work, there are three main charging rates: 3.7 kW (i.e. single-phase connection at 16 A), 7.4 kW (i.e. two-phase connection at 16 A) and 11 kW (i.e. three-phase connection at 16 A) [3]. Therefore, the full data set of sessions has been first split by user profile and second by charging rates to obtain the corresponding energy GMM, defined by the mixture weight (%), the mean (μ) and a standard deviation (σ). The energy GMM of the current study case are described in Appendix B. This improvement in the methodology respective to the initial method raised in [39] has been also introduced in the latest version of the open-source R package “evprof” [35].

Even though the charging power is now considered for building the energy models, it is not a variable to model with GMM since the charging power depends on the specific charging environment, like the characteristics of the charging infrastructure or the EV fleet. The methodology followed to simulate the charging power of charging sessions is further described in Section 3.3.

3.3. Simulation of charging sessions

The stochastic EV models built with the methodology of Section 3.2 allow estimating new charging sessions from the Gaussian distributions that describe every user profile in the different time cycles (e.g. day of the week, year, season, etc.) considered during the clustering process.

On the other hand, connection patterns and user needs vary from district to district. Thus, the share of the identified user profiles and the share of every charging rate (e.g. 3.7 kW, 7.4 kW, 11 kW, etc.) for every location (street, neighbourhood, district, etc.) has been used to obtain the final energy models that represent the charging profiles explained in Section 3.2.2.

The simulation process of EV sessions has been done on a daily basis, taking into account the time cycle of that day (if considered different time cycles), the number of sessions to simulate during this day, the share of user profiles relative to the total number of daily sessions, and the share of the three main charging rates (3.7 kW, 7.4 kW and 11 kW). Thus, the connection variables are estimated first with the connection GMM of the time cycle and the user profile. Second, the charging power is assigned to every session randomly considering the share of every charging rate over the total. Finally, the energy value is estimated using the energy GMM corresponding to the time cycle, the user profile and the charging power of the session.

The open-source R package "evsim" [40] collects the functions described above to simulate new EV sessions using the Gaussian models created with the "evprof" R package already mentioned in Section 3.2.

3.4. Sizing of the charging infrastructure

The charging sessions have been simulated considering that all of them would be assumed by the public charging infrastructure in Amsterdam. Thus, the required growth of the charging infrastructure has been calculated according to the simulated sessions.

Every charging station can handle only two simultaneously connected EVs since there are two sockets per charging station. Thus, it is necessary to first calculate the number of charging stations required according to the maximum number of simultaneous connections; and second, to allocate every incoming session to the available socket. This second step is important to afterwards simulate the Flexpower program since it is required to know how many vehicles are charging simultaneously in a charging station. These calculations have been done using R package "evsim" [40].

3.5. Simulation of flexpower

As already introduced in Section 1, Flexpower is a smart charging project currently deployed in Amsterdam. In its third development phase, the DSO sends to the CPO the maximum current per phase that the MSR can assume with a 15 minute resolution. Thus, every 15 min the CPO must compare the number of charging vehicles charging, their respective demand and the maximum capacity of the MSR. If the demand is higher than the maximum capacity, then this maximum current per phase at MSR level is split among all charging vehicles. At the same time, another physical constraint is present in the Amsterdam pilot. The public charging stations have two sockets of 16 A, while the grid connection has a maximum of 25 A. Then, a vehicle can charge at 16 A when it is alone in the charging station, but the maximum current will be reduced to 12 A when any phase of the charging station is shared. However, charging two single-phase vehicles or one single-phase vehicle and one two-phase vehicle would allow the maximum rate of 16 A per phase since the charging stations are smart enough to distribute phases among the two sockets.

Considering all these constraints, Algorithm 1 describes how Flexpower is simulated, considering a time resolution of 15 min like the DSO capacity signals. The nomenclature of variables used in Algorithm 1 is described in Table 2.

Algorithm 1 iterates over all time slots in the simulation time sequence to assign the available charging power to the connected vehicles, according to the DSO capacity signal. With this purpose, the simulated schedule of charging sessions (i.e. S), with the connection times, energy and power variables for every session, is expanded among all time slots to create a time-series table (i.e. SE) with the corresponding value of power and energy charged by every charging session after the simulation of Flexpower program. In order to better visualize the process, Appendix A includes Table A.1, which shows an example of a simulated schedule of sessions (S), and Table A.2, which shows an example of the same schedule but expanded in time (SE). The $Power$ and $Energy$ variables of the expanded schedule SE are initialized at 0 to be filled by Algorithm 1, while the $EnergyLeft$ variable corresponds to the $Energy$ value from the original schedule S.

For every time slot in the date and time sequence, first, the number of vehicles charging is calculated by filtering the expanded schedule SE to find all charging sessions charging at that specific time slot. This number of vehicles charging is used to calculate the maximum phase current per vehicle according to the MSR capacity limit sent by the DSO. Second, it is assigned to every charging station that is charging a vehicle a maximum current according to the number of phases used in the station. Then, the charging current of every session would be the minimum between the MSR and the station limits. Finally, the $Power$ and $Energy$ of every session for this time slot are calculated and updated to the schedule SE. The sessions are considered to be charging until their $EnergyLeft$ value is 0, i.e. they have already charged all their requirements.

Table 2
Nomenclature of Flexpower algorithm.

Parameter	Description
S	Schedule of charging sessions, see example in Table A.1
SE	Expanded schedule of charging sessions along all time slots, see example in Table A.2
$Power_{s,t}$	Charging power of session s at time slot t. Corresponds to a cell in SE and is defined during the iterations of Algorithm 1
$Energy_{s,t}$	Energy charged by session s at time slot t. Corresponds to a cell in SE and is defined during the iterations of Algorithm 1
$EnergyLeft_s$	Energy to be charged by session s. It is updated in SE during the iterations of Algorithm 1. The initial value corresponds to $Energy_s$ in schedule S
$Phases_s$	Number of power phases of session s (single-phase=1, two-phase=2 and three-phase=3). It is defined in S
T	Date and time sequence
ΔT	Time sequence resolution, i.e. time difference between values in T
$A_{s,t}$	Charging current (in amps) of the session s at timeslot t
$A_{max,msr,t}$	Maximum charging current for transformer msr at timeslot t
$A_{max,cs,t}$	Maximum charging current for charging station cs at timeslot t

4. Calculations

The calculations performed in this work can be differentiated into two main blocks: (1) modelling of EV user profiles, and (2) simulation of Flexpower. This section describes the steps followed in each block and their main outcomes to later analyse in the next section the results obtained from these simulations.

4.1. Amsterdam EV models

After submitting the real set of charging sessions described in Section 3.1.1 to the modelling process from Section 3.2, seven user profiles have been discovered on seven different time cycles corresponding to the days of the week.

The real data set of charging sessions described in Section 3.1.1 has been submitted to the clustering methodology exposed in Section 3.2.1. The clustering has been performed separately by day of the week, since no relevant difference has been detected among the months of the year, using the connection start time (i.e. arrival time) and the connection duration (in hours) for the bi-variate Gaussian Mixture Models (GMM) clustering. Since every cluster obtained has a characteristic

Input : expanded schedule of charging sessions SE, time sequence T, time sequence resolution ΔT, MSR capacity limits $A_{max,msr}$
Output: Modified schedule of charging sessions SE

for t in T **do**
  SE_t = sessions charging during timeslot t
  if $length(SE_t) = 0$ **then**
    next `// No sessions charging at this timeslot`
  end
  `/* Find the maximum charging current allowed by the MSR at this timeslot */`
  $A_{max,msr,t} = A_{max,msr}/length(SE_t)$
  `/* Find the maximum charging current allowed by every Charging Station */`
  CS_t, unique charging $Station$ names for sessions in SE_t
  for cs in CS_t **do**
    $S_{cs,t}$ = sessions charging in station cs at timeslot t
    $PH_{cs,t}$ = sum of $Phases$ used by sessions $S_{cs,t}$
    if $PH_{cs,t} \leq 3$ **then**
      $A_{max,cs,t} = 16$
    end
    else
      $A_{max,cs,t} = 12.5$
    end
  end
  `/* For every session set the maximum current, power and energy */`
  for s in SE_t **do**
    $cs = Station_s$
    $A_{s,t} = min(A_{max,msr,t}, A_{max,cs,t})$ `// Allowed charging current`
    $Power_{s,t} = (A_{s,t} \times 230 \times Phases_s)/1000$ `// Update` $Power$ `in` SE
    $PotentialEnergy = Power_{s,t} \times \Delta T$
    $Energy_{s,t} = min(Energy_{s,t}, el)$ `// Update` $Energy$ `in` SE
    $EnergyLeft_s = EnergyLeft_s - Energy_{s,t}$ `// Update` $EnergyLeft$ `in` SE
  end
end

Algorithm 1: Algorithm to simulate Flexpower

connection pattern (i.e. Gaussian distribution) that can be interpreted as generic daily human behaviour, the most similar clusters have been grouped resulting in seven different user profiles. The average values of the connection start time and the connection duration, with the corresponding behaviour interpretations, are described in Table 3 for each one of the seven EV user profiles identified. These average values are just descriptive since every user profile has a specific Gaussian distribution for every day of the week. This is seen in Fig. 3, which shows the classification of all charging sessions (i.e. a single points in the plot) into these user profiles for every day of the week independently. The bi-variate Gaussian Mixture Models associated to every user profile's clusters are described in Tables B.2–B.8 of Appendix B with the corresponding location and variance parameters.

Besides connection models, that only gather the temporal behaviours, every user profile has a specific energy requirement, that somehow is related to the connection duration. Moreover, as exposed in Section 3.3, Fig. 4 validates that the charging power has also a clear impact on the amount of energy charged by the vehicle, plotting the density of $Energy$ values for every different charging rate (i.e. 3.7, 7.4 or 11 kW) and user profile. On one hand, it is clear that the 3.7 kW sessions have a lower average energy consumption, but a lower variation as well since the density distribution is narrower than the other charging rates. On the other hand, the 11 kW sessions have considerably different distribution for short sessions like the Shortstay or Dinner sessions. For these reasons, the Energy Gaussian Mixture Models have been fitted separately for every user profile and charging rate. The statistic values of the energy GMM are included in Tables B.9–B.55 of Appendix B.

4.2. Simulation of charging sessions and flexpower

Since the objective is to assess the performance of Flexpower when different levels of EV penetration are given, an increase in the number of charging sessions has been simulated by applying a factor k between 2 and 7 over the current number of sessions per week (current values of weekly sessions are shown for every MSR in Fig. 5). The share of every user profile in every MSR is shown in Fig. 6, for every different time cycle (i.e. day of the week in this case). This figure shows how different the demand can be from neighbourhood to neighbourhood.

The charging power distribution has been assumed to be equal for all the MSR since no considerable differences have been observed between them. Thus, the share of every charging power used in the simulations, shown in Table 4, corresponds to the current charging power distribution in the city of Amsterdam during 2021.

After simulating the sessions in the 7 different scenarios of EV penetration (i.e. factor k from 1 to 7), the charging infrastructure (i.e. the number of charging stations) required to handle the corresponding EV demand has been calculated according to the methodology described in

Table 3
Amsterdam EV user profiles interpretations.

EV user profile	Average connection start time	Average connection duration (hours)	Behaviour interpretation
Dinner	18:28	2,8	Short connections during the evening
Shortstay	13:51	0,418	Short connection all over the day
Visit	11:32	4,84	Connections over the day with a high variability on both connection start and duration
Worktime	8:41	8,62	Morning connections with a duration about 8 h (working time)
Commuters	18:21	15	Afternoon connections until next morning
Home	14:20	18,9	Generally early-afternoon connections until next morning, but with high variability on both connection start and duration
Pillow	21:29	13,3	Night connections generally until next morning

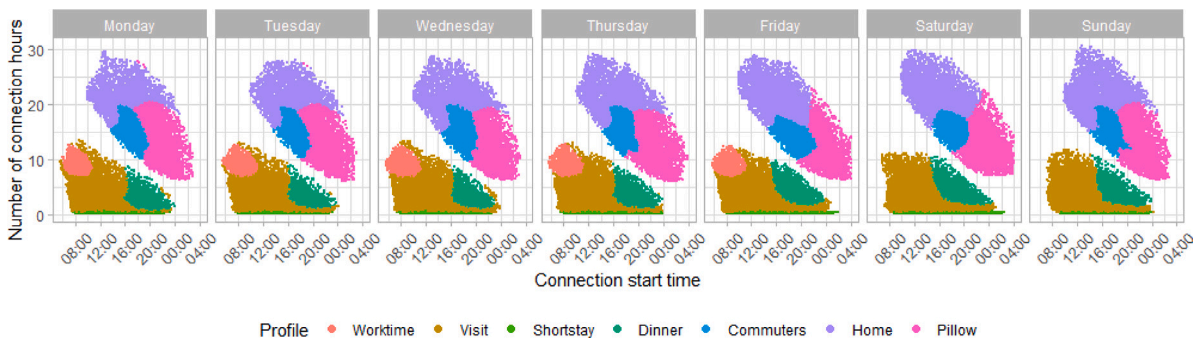

Fig. 3. Real data set of EV charging sessions classified into generic User profiles.

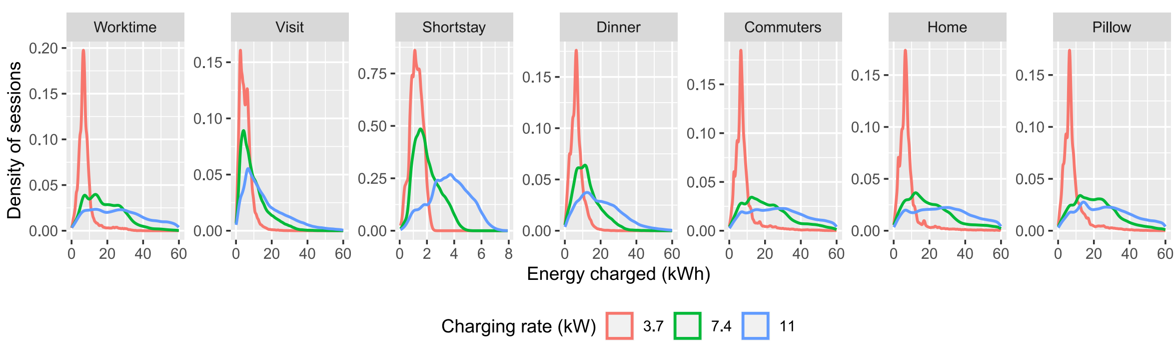

Fig. 4. Density curves for energy values of sessions belonging to every user profile and charging rate.

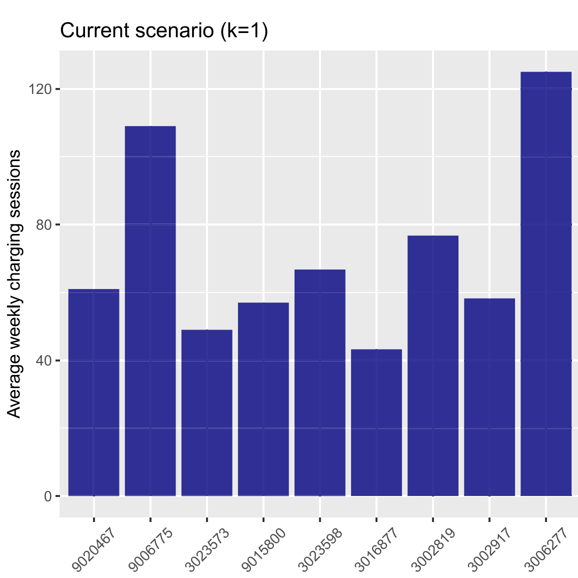

Fig. 5. Current weekly sessions for every MSR of the study.

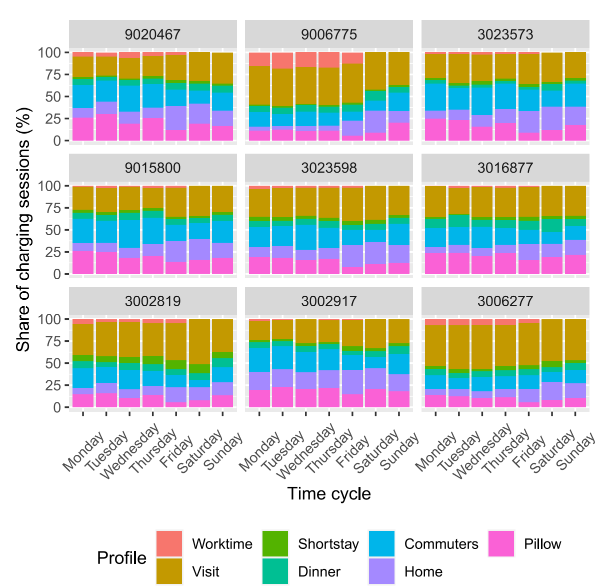

Fig. 6. Share of user profiles for every MSR of the study.

Table 4
Distribution of maximum charging powers in Amsterdam at the end of 2021.

Charging rate (kW)	Percentage of sessions (%)
3.7	29
7.4	20
11.0	51

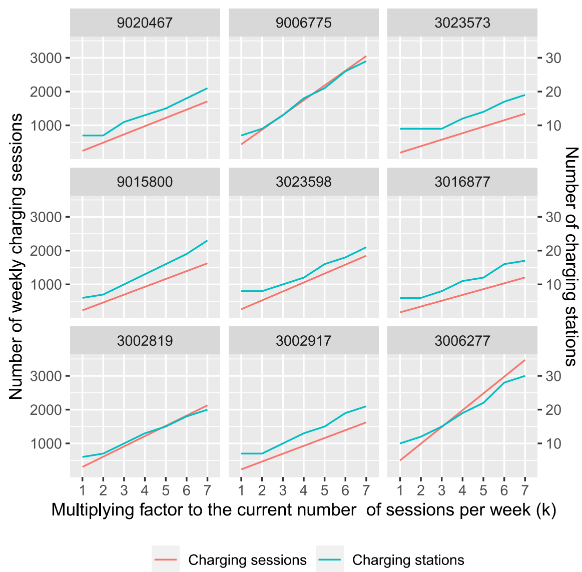

Fig. 7. Infrastructure growth according to sessions/week.

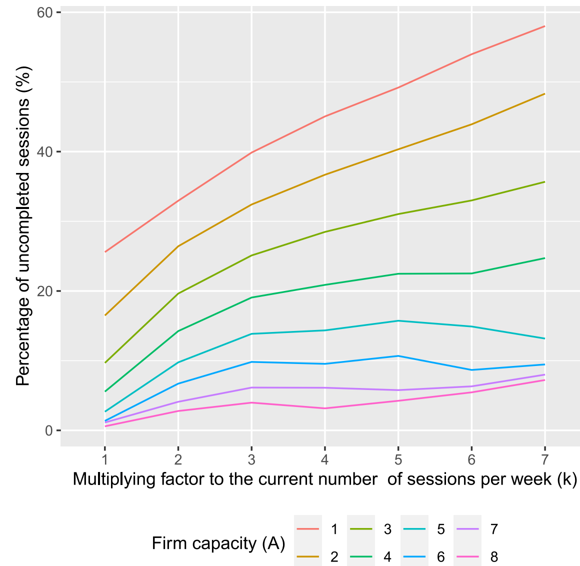

Fig. 8. Uncompleted sessions according to sessions/week.

Section 3.4. Finally, after simulating the charging sessions and sizing the charging infrastructure for every scenario, the different data sets of charging sessions have been submitted to the Flexpower algorithm described in Section 3.5.

5. Results and discussion

This section exposes the analysis of the simulation of Flexpower with different levels of EV penetration in the Amsterdam pilot. The analysis is done from the perspectives of the main stakeholders involved in the project: the Municipality, the Distribution System Operator (DSO), the Charging Point Operator (CPO) and the EV user. Specific performance indicators for each stakeholder have been defined and analysed for the different MSRs under multiple values of the $FirmCapacity$ in order to assess its impact.

5.1. Municipality perspective

The implementation of the Flexpower project aims to allow the installation of more charging stations downstream of MSRs that currently cannot reserve more power capacity for the EV charging infrastructure. Therefore, more charging sessions within the same maximum capacity are expected (see Table 1 in Section 3.1.2). Effectively, Fig. 7 shows that, in almost all MSR, the current charging infrastructure could double the number of weekly charging sessions. For k greater than 3, the growth of charging sessions has to be linked to the growth of the infrastructure.

Moreover, the municipality is not only interested in expanding the charging infrastructure but also to ensure a high-quality public charging service. The implementation of Flexpower, limiting the charging power during demand peak hours, could increase the number of uncompleted sessions at the end of their connection time, understanding 'uncompleted session' as the charging session that charges less than the original (i.e. simulated) energy requirement. If the percentage of uncompleted sessions grows significantly, the reputation of the public charging infrastructure could decrease resulting in a loss of confidence by the users followed by a reduction of its use. Fig. 8 represents the percentage of uncompleted sessions for every firm capacity according to the value of sessions per week k, across all MSRs. This figure shows how the global percentage of uncompleted sessions increases inversely with the magnitude of the firm capacity. Using only a Firm capacity of 1 A in the current scenario ($k = 1$) would suppose 25% of uncompleted sessions whereas a Firm capacity of 4 A, reduces it until a 5%, and the 25% with this Firm Capacity is reached when $k = 7$. Increasing Firm capacity to 6 A results in a percentage of uncompleted sessions around 10% for all the EV penetration scenarios.

5.2. DSO perspective

Fig. 9 shows, for every MSR, the maximum peak demand obtained in every scenario of the number of sessions (i.e. the value of k), relative to the corresponding existing maximum capacity (values of Table 1 in Section 3.1.2). For the current scenario ($k = 1$), most of MSRs have a peak demand between 20% and 40% of their maximum capacity reserved for public charging stations, except MSRs 9006775 and 3002819 reaching 40% and 50% of the capacity respectively.

For MSR 9006775, the peak demand is the same for all $Firmcapacity$ values from 1 to 5 A. This is because the MSR capacity limit for one specific day was higher than normal and the demand could also be high. This situation is represented in Fig. 10, for firm capacity values of 1 A (left) and 4 A (right), where the MSR limit is represented by the red dashed line, the static EV demand by the green dashed line, and the Flexpower EV demand by the green shaded line. In the right graph of Fig. 10, there is a visible gap between the MSR capacity limit and the Flexpower demand, even though the static demand is surpassing the MSR limit. This gap is also shown in Fig. 9, where the maximum values of the capacity level are between 80% and 90%, even for 7 times the current EV penetration. This gap in the power limitation of Flexpower is the result of two factors: (1) an important share of single-phase and two-phase vehicles in the system (i.e. 50% of sessions), which causes the limitation of phases that are not fully used, and (2) the representation of the MSR limit in power units (kW) considering a three-phase system. Therefore, the gap would decrease in the case of considering an EV fleet with a higher share of three-phase vehicles, which is expected to happen in the future.

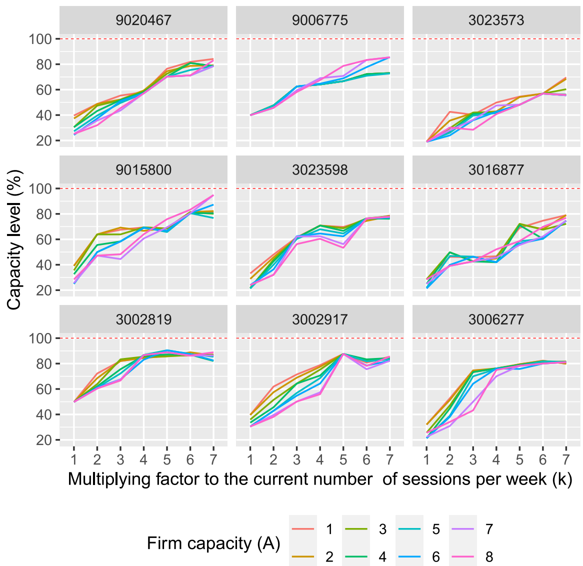

Fig. 9. MSR capacity reached according to sessions/week.

Another interesting result is that, for some MSRs, the maximum peak demand is higher for lower firm capacity values, when the power limitation is supposed to be harder. An example is the MSR 3023573. This is because during peak demand hours the limitation is higher with a low firm capacity and this results in a considerable rebound effect. This situation is represented in Fig. C.1 from Appendix C.

However, if we look at the peak reduction between the static and the flexible case, it is observed that the lower the firm capacity, the higher the peak reduction. Fig. 11 shows the reduction of the EV power demand achieved with Flexpower at the moment when it would have been the peak of demand without Flexpower. Therefore, the figure shows the reduction of demand in the flexible scenario with respect to the static scenario. It is visible that the peak reduction increases proportionally with the firm capacity, with the values varying depending on the MSR, but mainly constant over the number of sessions per week because the peak reduction is relative to the demand itself. For most MSRs, the peak reduction with a firm capacity of 1 A remains between 80% and 90%, with 4 A between 70% and 80%, with 6 A around 60% and with 8 A between 40% and 50%. Another important aspect is that the MSR capacity limits, which are created by the DSO, allow the rebound effect. As shown in Fig. 12, the MSR limit (red dashed line) is less constrained during valley hours (green shaded area) of the rest of the demand (blue shaded line) from households, offices, etc. This proves that the DSO calculates these EV capacity limits with the objective to obtain a flatter total demand profile. However, currently, this is not done in real-time but with a two-day ahead forecasting. This means that the forecasting must be done properly to avoid a rebound effect during peak demand hours, like the example seen in the left graph of Fig. C.1.

5.3. CPO perspective

The implementation of Flexpower will allow the charging infrastructure to grow and host more sessions. This will suppose more energy to be sold by the CPO, so higher income. However, the use of Flexpower also implies limiting charging power during peak demand hours, which could lead to a reduction of the energy charged for users with short connection times. Fig. 13 shows the percentage of the total amount of energy charged to all EV sessions relative to the originally required energy. In general, the total energy sold to users decreases considerably with firm capacity values lower than 4 amperes. In most cases, with a firm capacity value of 4 A and higher, the percentage of energy charged remains around 95% (red dashed line), which could be an acceptable value by the CPO.

For some MSRs the value of firm capacity plays a more critical role than others, depending on how the EV demand is limited by the DSO. For example, the affectation of different values of firm capacity in MSR 3002917 is similar, while in MSR 9015800 the reduction of energy charged highly depends on the firm capacity magnitude. The difference between the EV load and DSO constraints for MSRs 3002917 and 9015800 is shown in Figs. C.2 and C.3 from Appendix C respectively. Fig. C.2 shows how the EV demand in MSR 3002917 is lower than the maximum capacity, while Fig. C.3 shows that the EV demand in MSR 9015800 surpasses by far the MSR capacity limit. Another specific case is MSR 9006775, showing a non-linear evolution of the charged energy because the firm capacity only plays a role from higher k values since its capacity limit is mainly between the minimum and maximum capacity (see Fig. 10).

5.4. EV user perspective

The implementation of Flexpower will increase the charging infrastructure availability, allowing EV users to have charging stations on their streets and better accessibility to EV charging. Section 5.1 describes the number of uncompleted sessions, which could also be a service quality indicator from the EV user's point of view. However, the number of uncompleted sessions is represented from an aggregated perspective and, for a proper analysis of the impact's magnitude at an individual scale, it is necessary to analyse the proportion of the energy that is charged and missed by session. For this reason, Fig. 14 shows, according to the Firm capacity, the average value from all sessions' percentage of energy charged. The figure shows that a Firm capacity of minimum 5 A would have a reasonable impact on EV users, keeping the average charge around 95% of the energy requirements even in scenarios with high penetration of EVs.

Another critical concern about Flexpower from the user perspective is the impact that charging limitation will have on low-power users. Charging at 3.7 kW (i.e. single-phase EVs) could have a higher impact than charging at 11 kW (i.e. three-phase EVs) since with less time the latter can charge more. To answer this question, Fig. 15 shows the average percentage of energy charged for every charging rate and k scenario, considering a Firm capacity of 4 A (the value currently used). This figure shows that, in terms of the average percentage of energy charged, there is no relevant difference between the three different charging powers considered in the simulation. This is explained by the fact that high charging powers are related to larger batteries, which tend to charge more and require more energy. Moreover, for all k scenarios, the histogram of this variable results in a great majority of sessions charging 100% of their required energy, while the average values shown in Fig. 15 decrease due to outlying sessions with really high energy demand.

Finally, it is also interesting to see the impact by user profile, represented in Fig. 16. The most impacted user profiles are Dinner, Visit and Shortstay, in this order, due to their short connection times and the coincidence with the most constrained hours (i.e. peak demand hours). On the other hand, the users charging overnight like Commuters, Home and Pillow have a null impact with a firm capacity of 4 A for all scenarios, and a minimum impact with lower values of firm capacity.

5.5. Summary of main results

This section aims to summarize the results from all MSRs to extract general conclusions and recommendations at an aggregated city level. With this purpose, the average values of the four main indicators described in Section 4 have been calculated, each one representing the interest of the corresponding stakeholder in the Flexpower project. Currently, some of these indicators have a minimum or maximum value from which the Flexpower project would not be accepted by some of the stakeholders, even though they can change in the future.

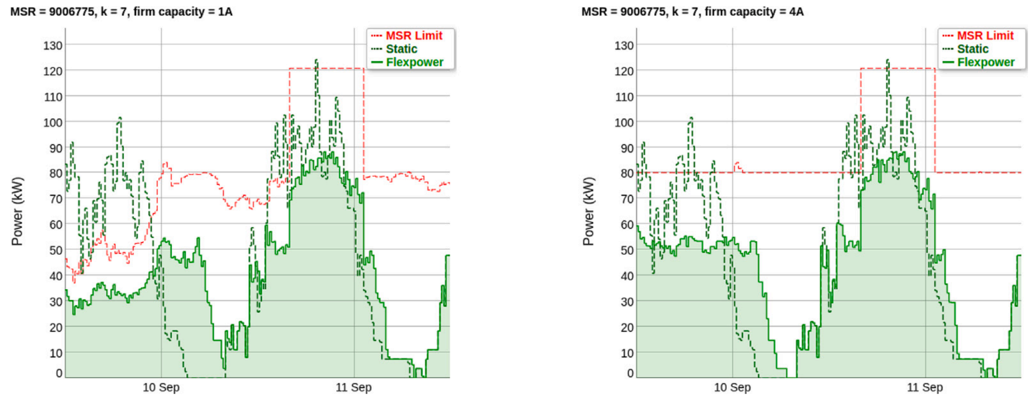

Fig. 10. MSR 9006775 with $k = 7$, comparing $FirmCapacity = 1$ (left) and $FirmCapacity = 4$ (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

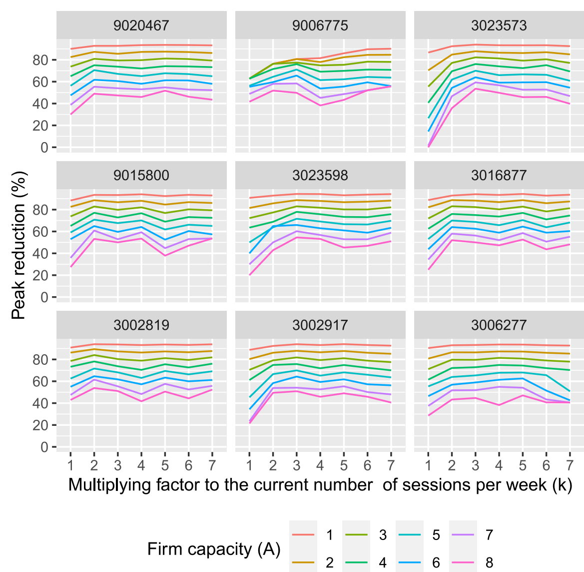

Fig. 11. MSR peak reduction according to sessions/week.

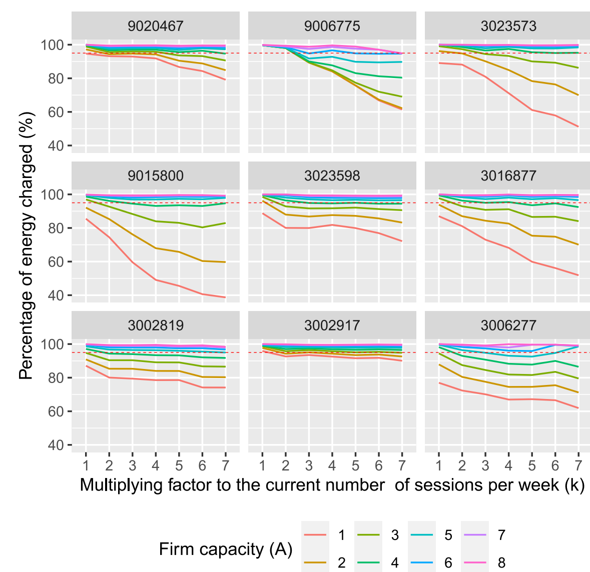

Fig. 13. Share of total energy charged according to sessions/week.

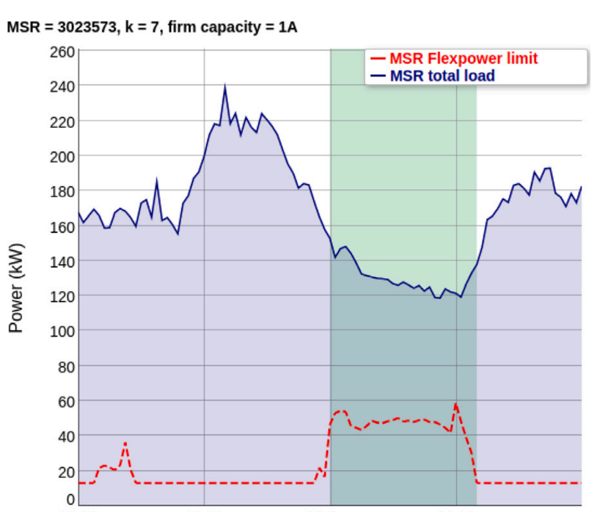

Fig. 12. MSR limit according to total power demand. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

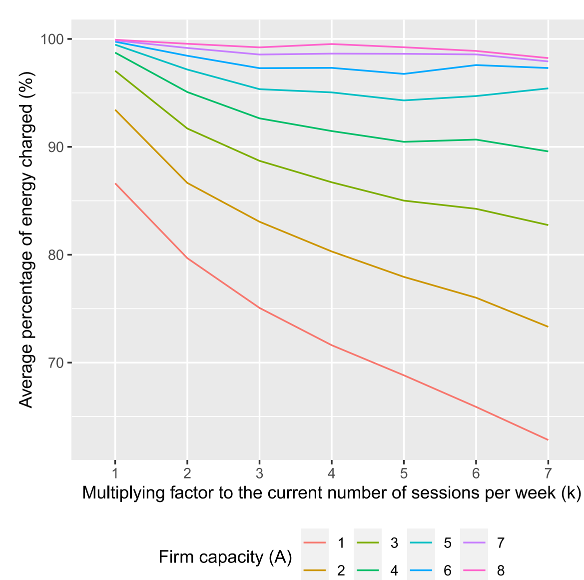

Fig. 14. Average percentage of energy charged according to sessions/week and firm capacity.

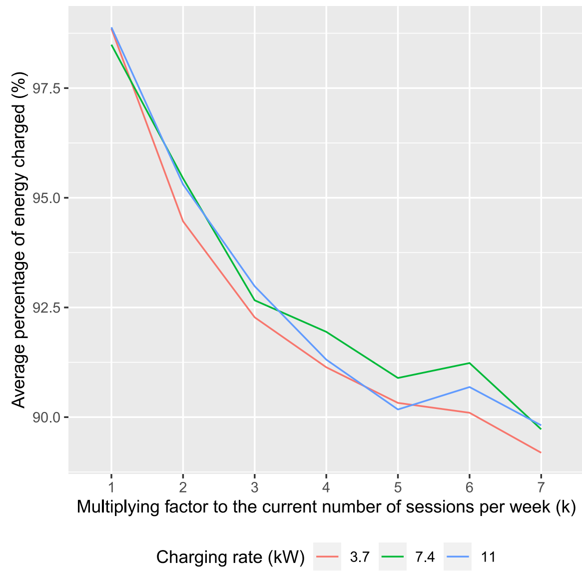

Fig. 15. Average percentage of energy charged according to sessions/week and charging power with FirmCapacity of 4 A.

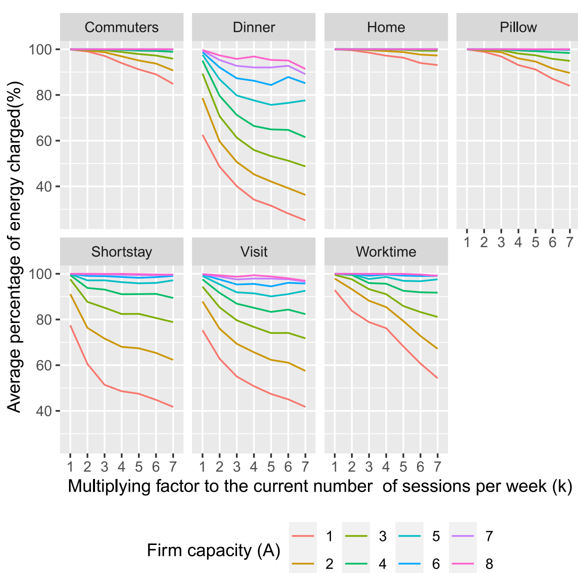

Fig. 16. Average percentage of energy charged according to sessions/week, firm capacity and user profile.

- Uncompleted sessions, in percentage, representing the Municipality's objective to ensure a high-quality charging service to Amsterdam EV users. The lower the better, and the acceptable maximum is assumed to be 10%.
- Demand peak reduction, in percentage, representing the grid congestion scenarios that the DSO wants to avoid. The higher the better, and the current acceptable minimum is assumed to be 0% since it is not a critical variable yet.
- Total energy charged, in percentage, being the share of energy that has been sold by the CPO to EV users from the total energy that users would have charged without Flexpower. The higher the better, and the acceptable minimum is assumed to be 95%.
- Average energy charged, in percentage, representing the Flexpower limitation impact on EV users at an individual scale. The higher the better, and the acceptable minimum is assumed to be 90%.

Firm capacity (A)	Uncompleted sessions (%)	Demand peak reduction (%)	Total energy charged (%)	Avg. energy charged (%)
1	26	89	89	87
2	16	81	96	93
3	10	72	99	97
4	6	63	99	99
5	3	55	100	99
6	1	46	100	100
7	1	36	100	100
8	1	27	100	100

Fig. 17. Summary of results from current EV penetration ($k = 1$).

These indicators are calculated for every scenario of firm capacity and EV penetration (k) and represented in coloured tables. Fig. 17 shows the indicators for the current EV penetration ($k = 1$), while the future scenarios with higher EV penetration are represented in Figs. D.1–D.6 in Appendix D. Since all variables are expressed in percentages, they go from 0 to 100%, but the cells' colour also depends on the minimum/maximum accepted values described above, representing with red colour the non-accepted situations and a red-to-green gradient for the positive scenarios. This type of representation lets to understand in a more comprehensive way the "warning" situations. For example, Fig. 17 (i.e. current scenario) shows that a Firm capacity of 1 A only provides an acceptable scenario for the DSO, and that the optimal value of Firm capacity would be 4 A (i.e. the actual configuration) to ensure a small impact on EV users but still a considerable demand peak reduction. However, for the future EV penetration scenarios, i.e. Figs. D.1–D.6, the recommended firm capacity value to ensure an equilibrated scenario for all stakeholders would go up to 6 A, where the percentage of uncompleted sessions remains around 10%, the demand peak reduction around 60%, the total energy sold higher than 98% and the average energy charged by users higher than 97%.

6. Conclusions, further research and recommendations

This section summarizes the main conclusions obtained in this work, as well as some recommendations that arise from the results.

The main conclusions obtained from simulating Flexpower in different scenarios of EV penetration can be summarized in the following points:

- The majority of MSRs analysed can accommodate twice the current number of EV sessions without requiring additional charging stations.
- When the CPO-DSO communication operates seamlessly, and Flexpower functions without interruptions, grid congestion can be avoided even as charging infrastructure grows.
- In the MSRs where the Flexpower project works properly, expanding the charging infrastructure can improve service availability for EV users.
- The actual firm capacity value of 4 A balances stakeholder interests effectively, allowing a peak demand reduction of approximately 70% with a minimal user impact of 6% of uncompleted sessions.
- For future scenarios, a general firm capacity value of 6 A is recommended, offering an optimal balance between peak demand reduction (60%), uncompleted sessions (10%), and high energy delivery efficiency (> 98%).
- Differences in charging rates (3.7 kW, 7.4 kW, 11 kW) have no significant impact on individual EV charging outcomes.

As a general conclusion, Flexpower proves to be a reliable peak-shaving tool for DSOs during peak demand hours, even considering high EV penetration in the current low-voltage distribution system. However, accurate demand forecasting remains crucial to avoid rebound effects and minimize the risk of real congestion.

Table A.1
Example of a simulated schedule of EV sessions S.

MSR	Station	Session	ConnectionTime	ConnectionHours	Phases	MaxPower	Energy
9020467	9020467CHS1	S1	05/09 08:15	0.77	1	3.7	2.84
9020467	9020467CHS2	S2	05/09 08:15	9.83	2	7.4	28.19
9020467	9020467CHS3	S3	05/09 10:45	4.83	2	7.4	2.71
9020467	9020467CHS4	S4	05/09 12:45	20.40	2	7.4	33.09
9020467	9020467CHS5	S5	05/09 13:45	4.18	2	7.4	7.30
9020467	9020467CHS6	S6	05/09 18:00	13.25	1	3.7	5.97

In terms of EV user impact, a recommendation for future studies could be to explore prioritization strategies based on user profiles, specially for short-connection user profiles (e.g., Visitors, Shortstay, Dinner).

Finally, note that the simulations of Flexpower considering high EV penetration scenarios have assumed that the MSR capacity limits sent by the DSO were identical to the capacity limits sent during September 2022. In that sense, updated data sets of charging sessions and MSR power demand would be crucial for proper simulations since the capacity limits may increase together with the EV demand. However, obtaining access to these data sets from the DSO or CPO is frequently challenging due to data privacy and confidentiality constraints.

Regular access to updated data sets of charging sessions is strongly recommended for more accurate insights. While the characteristics of specific EV user profiles may remain stable over time, periodic validation of EV models is essential to ensure the accuracy and relevance of the simulations.

CRediT authorship contribution statement

Marc Cañigueral: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rick Wolbertus:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Joaquim Meléndez:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marc Canigueral reports financial support was provided by Spanish Ministry of Education and Culture. Joaquim Melendez reports financial support was provided by Horizon Europe.

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Appendix A. Schedules of charging sessions

This appendix shows examples of the schedules of charging sessions used in Algorithm 1 to simulate Flexpower implementation.

Table A.2
Example of an expanded schedule of EV sessions SE.

Session	Station	Timeslot	Phases	Power	Energy	EnergyLeft
S1	9020467CHS1	05/09 06:15	1	0	0	2.84
S1	9020467CHS1	05/09 06:30	1	0	0	2.84
S1	9020467CHS1	05/09 06:45	1	0	0	2.84
S1	9020467CHS1	05/09 07:00	1	0	0	2.84
S1	9020467CHS1	05/09 07:15	1	0	0	2.84
S2	9020467CHS2	05/09 06:15	2	0	0	28.19
S2	9020467CHS2	05/09 06:30	2	0	0	28.19
S2	9020467CHS2	05/09 06:45	2	0	0	28.19

Appendix B. Amsterdam EV GMM models

The Gaussian Mixture Models clustering method parametrizes the statistic parameters of the Gaussian distributions found in the data through multiple iterations of the Expectation–Maximization (EM) algorithm. These parameters are the mixture weight (π), the means vector (μ) and a covariance matrix (Σ). After initialization, the EM algorithm iterates between Expectation–Maximization steps until the log-likelihood function of the model converges with the predefined tolerance. The main equations of the Expectation–Maximization process are detailed in Eqs. (B.1) to (B.7), and the corresponding nomenclature described in Table B.1.

The log-likelihood is computed with Eq. (B.1), referring to each data point as x_i, with i being from 1 to M, and the parameters of each cluster or Gaussian Model, being c being from 1 to K. $N(x_i|\mu_c, \Sigma_c)$ represents the multivariate Gaussian Mixture Model, defined in Eq. (B.2). The log-likelihood is the logarithmic expression of the weighted description of Gaussian mixture models among all data points. If the Gaussian equation fits the data well, the likelihood increases, so it is used to select the optimal result of several iterations.

$$\log\ p(X|\pi, \mu, \Sigma) = \sum_{i=1}^{M} \log(\sum_{c=1}^{K} \pi_c N(x_i|\mu_c, \Sigma_c)) \tag{B.1}$$

$$N(x_i, \mu_c, \Sigma_c) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_c|^{\frac{1}{2}}} exp(-\frac{1}{2}(x_i - \mu_c)^T \Sigma_c^{-1}(x_i - \mu_c)) \tag{B.2}$$

In the Expectation step, the probability of each data point being generated by each of the Gaussian models is computed. In contrast to the K-Means' hard assignments, the Expectation assignments are called soft assignments since we are using these probabilities known as responsibilities. Each probability or responsibility is calculated with Eq. (B.3). Therefore if x_i is very close to one Gaussian distribution c, it will obtain a high $r_i c$ value for this Gaussian and relatively low values otherwise.

$$r_{ic} = \frac{\pi_c N(x_i|\mu_c, \Sigma_c)}{\sum_{k=1}^{K} \pi_k N(x_i|\mu_k, \Sigma_k)} \tag{B.3}$$

In the Maximization step, the mixture weights (Eq. (B.5)), the mean (Eq. (B.6)) and the covariance (Eq. (B.7)) are updated for each Gaussian mixture model or cluster according to the total responsibility m_c allocated to each cluster (Eq. (B.4)).

$$m_c = \sum_{i} r_{ic} \tag{B.4}$$

$$\pi_c = \frac{m_c}{M} \tag{B.5}$$

Table B.1
Nomenclature of Expectation–Maximization algorithm.

Parameter	Description
X	Sample
M	Size of the sample
x	Data point from the sample
i	Index of the data point
K	Number of clusters (Gaussian models)
c	Index of the cluster
π	Weight of the model over the mixture
μ	Means vector of the Gaussian model
Σ	Covariance matrix of the Gaussian model
n	Number of dimensions of the Gaussian model (2 in this case)

Table B.2
Connection GMM — Time cycle: Monday.

User profile	Centroid (μ)	Covariance (Σ)		Share (%)
Dinner	2.90615 0.876571	0.008184 −0.015188	−0.015188 0.271821	100
Shortstay	2.602059 −0.844344	0.054892 −0.013443	−0.013443 0.113669	100
Visit	2.224958 0.648561	0.012919 −0.017804	−0.017804 0.615099	20
	2.647424 0.409364	0.036988 −0.042734	−0.042734 0.426892	46
	2.450714 1.60023	0.059209 −0.03352	−0.03352 0.132128	34
Worktime	2.159093 2.151399	0.016015 −0.006231	−0.006231 0.017814	100
Commuters	2.909311 2.622853	0.001833 −0.002482	−0.002482 0.005332	39
	2.854041 2.7055	0.00779 −0.007672	−0.007672 0.021309	61
Home	2.802377 3.089042	0.029315 −0.008855	−0.008855 0.014277	64
	2.616463 2.925533	0.019211 −0.01384	−0.01384 0.013821	36
Pillow	3.024335 2.697385	0.012213 −0.014331	−0.014331 0.057154	50
	3.056247 2.382308	0.006836 −0.012762	−0.012762 0.035988	50

$$\mu_c = \frac{1}{m_c} \sum_i r_{ic} x_i \tag{B.6}$$

$$\Sigma_c = \frac{1}{m_c} \sum_i r_{ic} (x_i - \mu_c)^T (x_i - \mu_c) \tag{B.7}$$

Following, the rest of this appendix exposes the statistical features of the bivariate GMM for the connection variables (i.e. connection start time and connection duration), in Tables B.2 to B.8, and the univariate GMM for the energy variable, in Tables B.9 to B.55. For the bivariate GMM, the first value of the vectors corresponds to the connection start time and the second one to the connection duration. All values are in logarithmic scale.

Table B.3
Connection GMM — Time cycle: Tuesday.

User profile	Centroid (μ)	Covariance (Σ)		Share (%)
Dinner	2.915739 0.991892	0.007222 −0.013563	−0.013563 0.203771	100
Shortstay	2.595682 −0.877011	0.055806 −0.014146	−0.014146 0.101967	100
Visit	2.274761 0.530679	0.020701 −0.026512	−0.026512 0.543125	26
	2.697359 0.412169	0.032097 −0.040317	−0.040317 0.462128	45
	2.428679 1.602524	0.056506 −0.027404	−0.027404 0.126708	29
Worktime	2.161591 2.154182	0.018226 −0.006287	−0.006287 0.018026	100
Commuters	2.853544 2.707496	0.007125 −0.006621	−0.006621 0.020018	61
	2.911855 2.619137	0.001783 −0.002441	−0.002441 0.005518	39
Home	2.623292 2.92207	0.018666 −0.013757	−0.013757 0.014303	34
	2.819282 3.073179	0.027405 −0.008251	−0.008251 0.013994	66
Pillow	3.058212 2.381142	0.006828 −0.013278	−0.013278 0.037803	50
	3.032819 2.675989	0.011879 −0.013404	−0.013404 0.056227	50

Table B.4
Connection GMM — Time cycle: Wednesday.

User profile	Centroid (μ)	Covariance (Σ)		Share (%)
Dinner	2.915956 0.979706	0.006567 −0.012189	−0.012189 0.202099	100
Shortstay	2.605417 −0.873139	0.054066 −0.012329	−0.012329 0.106951	100
Visit	2.469057 1.577391	0.057871 −0.028818	−0.028818 0.130551	28
	2.67724 0.398201	0.035844 −0.040479	−0.040479 0.432049	47
	2.248364 0.580657	0.016989 −0.023225	−0.023225 0.58306	24
Worktime	2.157691 2.154932	0.019779 −0.005807	−0.005807 0.018087	100
Commuters	2.913923 2.616466	0.002988 −0.003973	−0.003973 0.007209	38
	2.884976 2.713653	0.006782 −0.005749	−0.005749 0.023596	62
Home	2.662363 2.899304	0.021479 −0.016534	−0.016534 0.018084	44
	2.840337 3.086729	0.025366 −0.008999	−0.008999 0.014551	56
Pillow	3.083557 2.588354	0.007549 −0.007957	−0.007957 0.056774	49
	3.078029 2.343394	0.005544 −0.010729	−0.010729 0.032241	51

Table B.5
Connection GMM — Time cycle: Thursday.

User profile	Centroid (μ)	Covariance (Σ)		Share (%)
Dinner	2.916082 1.030949	0.007287 −0.012564	−0.012564 0.207311	100
Shortstay	2.627719 −0.872916	0.055625 −0.01074	−0.01074 0.107096	100
Visit	2.444955 1.60318	0.054289 −0.02414	−0.02414 0.124819	28
	2.265233 0.533386	0.017056 −0.022796	−0.022796 0.572466	24
	2.690537 0.431032	0.035126 −0.04257	−0.04257 0.448349	48
Worktime	2.16498 2.15764	0.018645 −0.005582	−0.005582 0.01937	100
Commuters	2.86405 2.764058	0.005729 −0.002486	−0.002486 0.019574	56
	2.919412 2.609813	0.002544 −0.003431	−0.003431 0.007533	44
Home	2.828282 3.082398	0.027628 −0.011494	−0.011494 0.015056	64
	2.663211 2.906163	0.020831 −0.015887	−0.015887 0.017075	36
Pillow	3.067254 2.588419	0.009803 −0.009799	−0.009799 0.055162	60
	3.076995 2.353319	0.006027 −0.012883	−0.012883 0.038617	40

Table B.6
Connection GMM — Time cycle: Friday.

User profile	Centroid (μ)	Covariance (Σ)		Share (%)
Dinner	2.927753 1.267123	0.008435 −0.015669	−0.015669 0.160917	100
Shortstay	2.689094 −0.845723	0.057665 −0.008531	−0.008531 0.115222	100
Visit	2.697067 0.520512	0.038664 −0.026562	−0.026562 0.400258	56
	2.409645 1.579068	0.047276 −0.01622	−0.01622 0.118676	25
	2.258562 0.476156	0.014785 −0.020624	−0.020624 0.550194	19
Worktime	2.166143 2.151984	0.01873 −0.004876	−0.004876 0.018589	100
Commuters	2.945413 2.684162	0.010853 −0.012398	−0.012398 0.028048	100
Home	2.703612 2.938624	0.026907 −0.01801	−0.01801 0.017656	20
	2.644204 3.156936	0.020781 −0.004694	−0.004694 0.008312	17
	2.897279 2.933279	0.008299 −0.00452	−0.00452 0.020621	62
Pillow	3.138736 2.325692	0.006657 −0.009075	−0.009075 0.035011	54
	3.146108 2.659584	0.006337 −0.008052	−0.008052 0.034012	46

Table B.7
Connection GMM — Time cycle: Saturday.

User profile	Centroid (μ)	Covariance (Σ)		Share (%)
Dinner	2.902284 1.365015	0.011843 −0.02312	−0.02312 0.15948	100
Shortstay	2.72743 −0.908894	0.055581 0.002613	0.002613 0.099182	100
Visit	2.231113 2.113825	0.018042 −0.010755	−0.010755 0.022106	3
	2.345898 0.321927	0.020576 −0.031789	−0.031789 0.488004	18
	2.708548 0.353022	0.035505 −0.008343	−0.008343 0.326618	47
	2.559902 1.332923	0.035843 −0.018856	−0.018856 0.201322	33
Commuters	2.911365 2.79135	0.012366 −0.012574	−0.012574 0.028159	100
Home	2.546875 3.251953	0.011942 −0.001784	−0.001784 0.004562	8
	2.853921 2.99875	0.016394 −0.006766	−0.006766 0.020225	72
	2.578714 3.07055	0.015061 −0.007194	−0.007194 0.00878	19
Pillow	3.112993 2.586651	0.007507 −0.005299	−0.005299 0.040104	88
	3.204042 2.228861	0.003842 −0.000944	−0.000944 0.016972	12

Table B.8
Connection GMM — Time cycle: Sunday.

User profile	Centroid (μ)	Covariance (Σ)		Share (%)
Dinner	2.859852 1.243677	0.01202 −0.021409	−0.021409 0.169777	100
Shortstay	2.699098 −0.922504	0.042817 −0.006393	−0.006393 0.094184	100
Visit	2.490542 1.968693	0.039866 −0.016501	−0.016501 0.04973	7
	2.682302 0.423113	0.034394 −0.033529	−0.033529 0.351487	47
	2.586016 1.302041	0.032118 −0.014735	−0.014735 0.149935	31
	2.333055 0.493641	0.019582 −0.050075	−0.050075 0.510673	16
Commuters	2.852936 2.742745	0.007078 −0.005937	−0.005937 0.02089	55
	2.897143 2.636487	0.012786 −0.016074	−0.016074 0.02178	45
Home	2.620554 2.906539	0.017555 −0.012306	−0.012306 0.012196	41
	2.801567 3.105664	0.025445 −0.009202	−0.009202 0.017436	59
Pillow	3.052354 2.66243	0.009105 −0.010265	−0.010265 0.054658	57
	3.057295 2.363174	0.007323 −0.013692	−0.013692 0.03684	43

Table B.9
Energy GMM — Time cycle: Monday, User profile: Worktime.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.171579	0.273411	11
	1.926286	0.273411	83
	2.780341	0.273411	7
7.4	1.441493	0.232724	4
	2.039606	0.232724	18
	2.671234	0.232724	30
	3.279565	0.232724	27
	3.280311	0.232724	20
11	1.77521	0.331344	9
	2.688591	0.392355	29
	3.28925	0.174041	19
	3.626921	0.160194	26
	3.965773	0.092573	14
	4.125019	0.041119	4

Table B.10
Energy GMM — Time cycle: Monday, User profile: Visit.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.081093	0.189728	4
	0.890668	0.296225	27
	1.306538	0.19794	14
	1.588346	0.145296	14
	1.856218	0.11094	19
	2.119571	0.163025	20
	2.499017	0.083861	3
7.4	1.17271	0.38776	26
	1.869486	0.310054	32
	2.574977	0.292072	33
	3.158822	0.140989	9
11	0.855169	0.22689	4
	1.730613	0.378774	20
	2.073448	0.213369	15
	2.44397	0.150056	13
	2.74435	0.138939	13
	3.079792	0.168286	14
	3.451959	0.166696	17
	3.753966	0.096707	5

Table B.11
Energy GMM — Time cycle: Monday, User profile: Shortstay.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	−0.860226	0.217848	8
	−0.124081	0.209308	24
	0.063342	0.185919	12
	0.195338	0.100148	17
	0.416844	0.086968	23
	0.594035	0.066683	14
	0.731726	0.014009	2
7.4	−0.167996	0.104911	8
	0.136737	0.104911	15
	0.436761	0.104911	23
	0.695869	0.104911	20
	0.961176	0.104911	16
	1.233334	0.104911	17
11	−0.007754	0.095729	3
	0.615876	0.294919	17
	1.06463	0.132487	22
	1.323474	0.091867	20
	1.526953	0.086496	21
	1.688666	0.058297	14
	1.800562	0.025718	3

Table B.12
Energy GMM — Time cycle: Monday, User profile: Dinner.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.358421	0.169327	4
	1.107533	0.337466	25
	1.5258	0.167266	22
	1.843163	0.107609	26
	2.141308	0.164055	22
	2.486009	0.045353	2
7.4	0.813069	0.20754	3
	1.4118	0.20754	14
	1.940671	0.20754	30
	2.427294	0.20754	36
	2.921834	0.20754	18
11	1.484966	0.366127	11
	2.110163	0.292354	17
	2.430252	0.162947	15
	2.679002	0.132762	14
	2.973907	0.136237	19
	3.313875	0.146608	20
	3.604156	0.072681	4

Table B.13
Energy GMM — Time cycle: Monday, User profile: Commuters.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.987202	0.253257	10
	1.530403	0.159849	16
	1.8653	0.089981	19
	2.055209	0.157739	19
	2.191557	0.420463	33
	3.183334	0.101226	2
7.4	1.935936	0.419316	23
	2.746574	0.277678	35
	3.334398	0.243034	36
	3.851481	0.080791	6
11	1.952648	0.391363	14
	2.831681	0.310344	27
	3.252189	0.171361	15
	3.595927	0.166648	27
	3.94306	0.108928	13
	4.136201	0.044388	4

Table B.14
Energy GMM — Time cycle: Monday, User profile: Home.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.023832	0.325169	16
	1.555933	0.16483	17
	1.891151	0.113105	26
	2.154169	0.207525	31
	2.840015	0.320813	9
7.4	1.988837	0.56826	28
	2.690594	0.271386	28
	3.338188	0.250544	37
	3.923863	0.090518	7
11	2.016964	0.490128	20
	2.942442	0.28177	23
	3.365381	0.175815	20
	3.715689	0.172577	27
	4.047439	0.078934	10

Table B.15
Energy GMM — Time cycle: Monday, User profile: Pillow.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.06881	0.308327	15
	1.538233	0.164438	16
	1.806623	0.077033	14
	1.933371	0.081621	17
	2.149771	0.11446	16
	2.530188	0.272835	19
	3.200928	0.091808	3
7.4	2.03044	0.528638	26
	2.626175	0.216021	20
	3.042619	0.167019	19
	3.397277	0.202044	31
	3.829945	0.083809	4
11	1.893113	0.36666	12
	2.470427	0.225744	9
	2.731987	0.155008	12
	3.090993	0.133316	14
	3.315706	0.099336	11
	3.490053	0.084408	11
	3.671606	0.085671	11
	3.89921	0.109176	14
	4.112621	0.0643	6

Table B.16
Energy GMM — Time cycle: Tuesday, User profile: Worktime.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.08728	0.199401	7
	1.551971	0.1568	20
	1.877632	0.098466	29
	2.112914	0.154842	33
	2.531366	0.333756	12
7.4	1.656559	0.250841	10
	2.023304	0.13779	13
	2.602858	0.205921	34
	3.033565	0.132848	16
	3.350834	0.13743	24
	3.677209	0.06731	4
11	2.08906	0.490065	21
	2.797495	0.276756	21
	3.299043	0.179151	21
	3.695085	0.189329	28
	4.053491	0.079072	8

Table B.17
Energy GMM — Time cycle: Tuesday, User profile: Visit.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.019547	0.154907	3
	0.685209	0.27714	16
	1.000841	0.177749	13
	1.289773	0.122772	12
	1.518369	0.102475	12
	1.725932	0.09185	11
	1.897689	0.09426	15
	2.143216	0.154398	16
	2.480869	0.054515	2
7.4	0.913773	0.302748	15
	1.504288	0.239929	24
	2.008088	0.210392	23
	2.550009	0.258822	31
	3.10587	0.125343	8
11	0.847233	0.214733	5
	1.615904	0.315826	17
	1.944342	0.161579	12
	2.243963	0.132156	11
	2.468594	0.120787	11
	2.717883	0.12033	12
	3.01162	0.144888	12
	3.379346	0.1708	16
	3.705264	0.091537	4

Table B.18
Energy GMM — Time cycle: Tuesday, User profile: Shortstay.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	−1.054353	0.10667	3
	−0.614652	0.184506	6
	−0.106246	0.166958	30
	0.184074	0.107098	24
	0.408302	0.093803	27
	0.603393	0.050473	9
	0.697841	0.015247	1
7.4	−0.176043	0.108204	8
	0.124438	0.108204	17
	0.417208	0.108204	22
	0.667159	0.108204	20
	0.933147	0.108204	18
	1.203047	0.108204	15
11	0.010129	0.101311	3
	0.519625	0.251924	14
	1.0806	0.179876	33
	1.390212	0.120784	29
	1.599102	0.084646	15
	1.744541	0.042225	6

Table B.19
Energy GMM — Time cycle: Tuesday, User profile: Dinner.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.965404	0.373687	18
	1.577843	0.207525	29
	1.854195	0.100838	20
	2.10453	0.175168	28
	2.477557	0.059866	4
7.4	1.483534	0.525629	17
	2.058346	0.318773	39
	2.584308	0.233177	36
	3.045736	0.10795	8
11	1.248806	0.277857	5
	1.932534	0.281704	16
	2.392931	0.169684	15
	2.649384	0.119076	12
	2.856342	0.106245	11
	3.106513	0.122944	18
	3.406317	0.138093	20
	3.678147	0.043908	2

Table B.20
Energy GMM — Time cycle: Tuesday, User profile: Commuters.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.970495	0.20724	9
	1.536978	0.196738	21
	1.877454	0.08997	18
	2.055368	0.165348	20
	2.221733	0.391076	28
	3.161608	0.156491	4
7.4	1.984349	0.419171	24
	2.689788	0.251996	30
	3.283485	0.249061	39
	3.826536	0.08222	7
11	1.968728	0.359497	15
	2.651195	0.226742	15
	3.038332	0.187383	14
	3.298975	0.141721	15
	3.545583	0.11792	16
	3.832547	0.133885	19
	4.073983	0.072752	7

Table B.21
Energy GMM — Time cycle: Tuesday, User profile: Home.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.972279	0.242452	11
	1.917299	0.087702	12
	1.921595	0.364888	72
	2.969089	0.201011	5
7.4	1.948314	0.632002	27
	2.653681	0.324939	35
	3.339299	0.260065	32
	3.929502	0.09389	6
11	2.061703	0.483798	22
	2.897094	0.265791	22
	3.338283	0.17922	20
	3.703313	0.180134	29
	4.046617	0.074301	8

Table B.22
Energy GMM — Time cycle: Tuesday, User profile: Pillow.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.069973	0.309213	16
	1.553681	0.159182	17
	1.809805	0.065799	11
	1.908431	0.082997	16
	2.119301	0.134839	18
	2.524579	0.298336	20
	3.229709	0.108315	3
7.4	1.260579	0.264717	4
	1.995831	0.274242	15
	2.513433	0.177566	17
	2.890302	0.160644	19
	3.228864	0.149854	24
	3.556283	0.173679	18
	3.904282	0.044153	2
11	1.870273	0.369803	11
	2.505673	0.264935	12
	2.749722	0.167996	12
	3.112514	0.136494	13
	3.363156	0.117176	15
	3.619828	0.117814	18
	3.914513	0.117336	15
	4.129545	0.049098	4

Table B.23
Energy GMM — Time cycle: Wednesday, User profile: Worktime.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.932523	0.168769	5
	1.441405	0.180566	14
	1.628252	0.084702	8
	1.827439	0.068618	16
	1.963054	0.067891	18
	2.168064	0.108333	17
	2.279299	0.360121	20
	3.148222	0.054449	1
7.4	1.489265	0.178523	4
	1.996225	0.178523	18
	2.54588	0.178523	25
	2.942738	0.178523	21
	3.322037	0.178523	17
	3.34612	0.178523	15
11	1.796727	0.300342	11
	2.512704	0.26119	16
	2.891503	0.214175	14
	3.274137	0.160904	19
	3.613044	0.178668	25
	3.966763	0.099403	12
	4.149179	0.023549	2

Table B.24
Energy GMM — Time cycle: Wednesday, User profile: Visit.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.043684	0.131754	2
	0.783831	0.307252	23
	1.120862	0.197528	14
	1.406694	0.145221	12
	1.638048	0.129478	12
	1.854201	0.103118	16
	2.111769	0.15495	18
	2.44555	0.063968	2
7.4	0.900947	0.331671	15
	1.365477	0.208968	16
	1.689925	0.166936	12
	1.981101	0.155636	15
	2.314872	0.17071	16
	2.716092	0.222803	21
	3.159213	0.108559	6
11	0.818765	0.206374	4
	1.590892	0.341296	16
	1.943702	0.178965	14
	2.263208	0.13778	12
	2.502227	0.120851	11
	2.740656	0.122025	11
	3.009582	0.134042	11
	3.344072	0.167731	16
	3.664745	0.094606	5

Table B.25
Energy GMM — Time cycle: Wednesday, User profile: Shortstay.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	−0.762247	0.272689	8
	−0.095884	0.182892	32
	0.166029	0.107644	20
	0.431678	0.110183	32
	0.640681	0.047893	6
7.4	−0.153676	0.176866	12
	0.314928	0.211922	31
	0.699771	0.217183	37
	1.095994	0.111553	16
	1.301634	0.034772	3
11	0.007534	0.101901	3
	0.596892	0.282773	16
	1.068402	0.144448	24
	1.368406	0.122486	32
	1.611061	0.089503	21
	1.77474	0.038594	4

Table B.26
Energy GMM — Time cycle: Wednesday, User profile: Dinner.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.081134	0.412974	23
	1.568519	0.175635	23
	1.842891	0.105598	20
	2.098298	0.171015	30
	2.465851	0.056704	4
7.4	0.858155	0.248412	4
	1.974846	0.384342	48
	2.467693	0.177837	29
	2.868517	0.153815	15
	3.152018	0.06818	4
11	0.925559	0.150745	2
	1.851865	0.372578	19
	2.392869	0.193068	16
	2.690598	0.135468	15
	2.946509	0.111316	14
	3.157793	0.106631	12
	3.400045	0.125366	17
	3.652566	0.069844	4

Table B.27
Energy GMM — Time cycle: Wednesday, User profile: Commuters.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.974382	0.222606	9
	1.572238	0.212203	21
	1.876431	0.093168	19
	2.092087	0.153416	19
	2.242761	0.405484	29
	3.185298	0.132381	3
7.4	1.991066	0.444096	24
	2.689202	0.274274	29
	3.295246	0.260673	41
	3.860751	0.091589	7
11	1.93847	0.358336	14
	2.73041	0.277602	21
	3.168964	0.182196	17
	3.444237	0.139687	17
	3.748905	0.153113	22
	4.045471	0.090776	9

Table B.28
Energy GMM — Time cycle: Wednesday, User profile: Home.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.274792	0.407832	26
	1.892391	0.078451	9
	1.992101	0.298026	58
	2.948294	0.244568	7
7.4	2.013595	0.547442	28
	2.652766	0.294474	29
	3.308731	0.278782	37
	3.938944	0.106558	6
11	1.984671	0.495345	19
	2.93058	0.312272	27
	3.37953	0.170025	20
	3.725338	0.166736	24
	4.040498	0.086177	9

Table B.29
Energy GMM — Time cycle: Wednesday, User profile: Pillow.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.235186	0.412497	24
	1.533515	0.132672	8
	1.68851	0.148832	6
	1.828766	0.069232	14
	1.956934	0.083036	13
	2.16411	0.131004	16
	2.568789	0.274005	18
	3.187863	0.070768	2
7.4	1.865957	0.434002	16
	2.679837	0.300739	35
	3.292382	0.231554	43
	3.797981	0.107325	6
11	1.974255	0.40714	13
	2.730375	0.247951	25
	3.293054	0.181926	24
	3.684376	0.187769	28
	4.050304	0.097406	10

Table B.30
Energy GMM — Time cycle: Thursday, User profile: Worktime.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.943028	0.210794	6
	1.649272	0.225486	32
	1.78876	0.044694	6
	1.87853	0.042093	8
	1.963522	0.056919	12
	2.162259	0.113753	24
	2.52678	0.28088	11
	3.106057	0.058609	2
7.4	1.233812	0.225108	4
	1.961623	0.225108	19
	2.606355	0.225108	33
	3.243187	0.225108	24
	3.244404	0.225108	20
11	2.036793	0.407149	20
	2.817786	0.287302	24
	3.284006	0.175463	19
	3.650285	0.189192	27
	4.012437	0.088769	10

Table B.31
Energy GMM — Time cycle: Thursday, User profile: Visit.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.064851	0.180047	4
	0.729016	0.266838	17
	0.997853	0.161433	12
	1.287469	0.112199	11
	1.502576	0.100115	12
	1.712912	0.096032	12
	1.891601	0.090732	14
	2.130888	0.154076	17
	2.476482	0.057542	2
7.4	0.978084	0.350196	19
	1.518246	0.21981	19
	1.89834	0.181069	15
	2.242276	0.187117	18
	2.679177	0.229667	23
	3.138528	0.102419	6
11	0.764842	0.17862	3
	1.539884	0.347929	15
	1.904264	0.166969	13
	2.223486	0.130701	11
	2.465106	0.126429	12
	2.708912	0.132292	13
	3.026026	0.157949	14
	3.407878	0.173907	16
	3.739998	0.072142	3

Table B.32
Energy GMM — Time cycle: Thursday, User profile: Shortstay.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	−0.812987	0.224338	8
	−0.013359	0.232277	47
	0.342768	0.134767	29
	0.564178	0.083859	16
7.4	0.015078	0.228429	24
	0.448043	0.176996	32
	0.865373	0.179418	32
	1.200598	0.089997	12
11	−5.7e−05	0.099586	3
	0.638956	0.304351	18
	1.020899	0.109867	16
	1.257925	0.096653	21
	1.454244	0.085023	19
	1.632916	0.078424	18
	1.776074	0.040245	5

Table B.33
Energy GMM — Time cycle: Thursday, User profile: Dinner.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.03482	0.401456	22
	1.623443	0.191532	27
	1.868762	0.098138	19
	2.1155	0.171578	27
	2.460298	0.077804	5
7.4	0.841336	0.217909	3
	1.848726	0.39223	31
	2.232346	0.246114	22
	2.577821	0.181988	28
	2.977973	0.131752	13
	3.213106	0.058288	3
11	0.999106	0.143109	2
	1.908494	0.370549	19
	2.429831	0.173691	16
	2.707558	0.113661	14
	2.951527	0.106088	13
	3.143408	0.111265	12
	3.372214	0.13247	19
	3.622484	0.067242	5

Table B.34
Energy GMM — Time cycle: Thursday, User profile: Commuters.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.982737	0.230391	9
	1.563351	0.192191	22
	1.864163	0.083316	18
	2.063399	0.132134	18
	2.239511	0.261094	26
	3.009997	0.212324	7
7.4	2.05384	0.479113	26
	2.743198	0.264027	30
	3.318618	0.229954	37
	3.834686	0.085682	7
11	1.881986	0.340182	10
	2.541995	0.26506	13
	2.867568	0.187757	11
	3.13077	0.123385	11
	3.329862	0.091184	10
	3.497851	0.083336	11
	3.678698	0.092646	14
	3.923226	0.105981	15
	4.115036	0.053884	4

Table B.35
Energy GMM — Time cycle: Thursday, User profile: Home.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.041258	0.335345	17
	1.550499	0.152718	16
	1.894931	0.111904	23
	2.142122	0.230798	35
	2.921393	0.295131	8
7.4	2.045437	0.57228	30
	2.649663	0.274235	25
	3.291217	0.271721	38
	3.892539	0.107807	6
11	1.872551	0.404465	14
	2.695708	0.319523	17
	3.06378	0.196393	15
	3.344416	0.116571	13
	3.584634	0.105567	16
	3.847418	0.129053	18
	4.092445	0.07162	6

Table B.36
Energy GMM — Time cycle: Thursday, User profile: Pillow.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.053641	0.302739	13
	1.529498	0.171202	16
	1.840559	0.08907	21
	2.045172	0.143863	20
	2.438895	0.334676	27
	3.230904	0.099488	3
7.4	2.076857	0.507819	24
	2.611527	0.199497	19
	3.036044	0.172717	21
	3.385007	0.200029	32
	3.822133	0.090096	5
11	1.97716	0.377784	13
	2.558039	0.202443	10
	2.760162	0.158809	11
	3.058748	0.119004	11
	3.270275	0.090047	11
	3.451627	0.082691	11
	3.64068	0.095276	14
	3.888088	0.120134	15
	4.110992	0.063326	6

Table B.37
Energy GMM — Time cycle: Friday, User profile: Worktime.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.968739	0.161193	5
	1.589399	0.234315	29
	1.893768	0.11348	28
	2.148784	0.153799	30
	2.706832	0.236145	8
7.4	1.997139	0.3787	26
	2.704396	0.228472	30
	3.28747	0.209787	43
11	2.100851	0.48646	19
	2.828387	0.289831	23
	3.306575	0.170363	22
	3.669443	0.18935	26
	4.029803	0.085525	10

Table B.38
Energy GMM — Time cycle: Friday, User profile: Visit.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.129089	0.169711	4
	0.572284	0.169711	7
	0.973802	0.169711	19
	1.378027	0.169711	19
	1.542699	0.169711	7
	1.854163	0.169711	16
	1.862802	0.169711	17
	2.247885	0.169711	11
7.4	1.018988	0.333332	17
	1.575121	0.244413	22
	2.031239	0.219792	22
	2.553899	0.25876	32
	3.107559	0.132923	8
11	0.932611	0.203074	4
	1.621974	0.299704	15
	2.007562	0.168284	14
	2.303488	0.129093	11
	2.535275	0.118318	12
	2.767661	0.116249	12
	3.037096	0.140812	13
	3.374486	0.160148	16
	3.686605	0.088503	4

Table B.39
Energy GMM — Time cycle: Friday, User profile: Shortstay.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	−0.937694	0.076198	2
	−0.5764	0.17536	7
	−0.094325	0.168184	26
	0.089839	0.04761	7
	0.217061	0.054153	8
	0.39262	0.10455	30
	0.610397	0.062202	17
	0.724956	0.016515	3
7.4	−0.149983	0.188143	11
	0.221032	0.141386	18
	0.560698	0.13997	29
	0.922416	0.155967	28
	1.202464	0.076914	9
	1.333426	0.033723	5
11	0.002334	0.100143	2
	0.644798	0.291964	18
	1.016653	0.108993	14
	1.190441	0.064233	9
	1.309756	0.049776	9
	1.429254	0.06542	15
	1.592405	0.077387	18
	1.748016	0.04947	11
	1.836879	0.021723	3

Table B.40
Energy GMM — Time cycle: Friday, User profile: Dinner.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.102256	0.366708	18
	1.670272	0.224065	22
	1.895147	0.105045	24
	2.193818	0.151503	26
	2.551497	0.112093	10
7.4	1.349076	0.37921	8
	2.086009	0.257727	25
	2.543335	0.184394	34
	2.988675	0.172038	27
	3.309604	0.076302	6
11	2.0869	0.540162	22
	2.680928	0.31528	30
	3.118135	0.145417	15
	3.413472	0.156686	26
	3.729909	0.100246	8

Table B.41
Energy GMM — Time cycle: Friday, User profile: Commuters.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.016421	0.293672	12
	1.504157	0.154661	12
	1.873723	0.096362	22
	2.104537	0.152897	19
	2.233003	0.423762	30
	3.191443	0.162585	5
7.4	1.17756	0.185683	2
	1.982252	0.309802	15
	2.542143	0.182943	17
	2.885526	0.142358	17
	3.170284	0.118204	15
	3.427776	0.131114	21
	3.768734	0.108258	9
	3.966508	0.045762	3
11	1.787604	0.288967	7
	2.429193	0.293813	12
	2.799374	0.171648	12
	3.090952	0.138768	11
	3.282247	0.101802	11
	3.475109	0.08966	13

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Table B.41 (*continued*).

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
	3.70862	0.117659	20
	3.985759	0.088152	12
	4.149102	0.031346	2

Table B.42
Energy GMM — Time cycle: Friday, User profile: Home.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.064883	0.328607	16
	1.564695	0.166677	16
	1.850132	0.095658	15
	1.989653	0.138527	17
	2.177263	0.253354	28
	3.052051	0.270198	8
7.4	2.081696	0.592659	33
	2.694858	0.284212	26
	3.314061	0.26641	36
	3.90728	0.100226	6
11	1.996901	0.436171	16
	2.714507	0.250026	15
	3.060396	0.170613	13
	3.344367	0.129286	15
	3.578259	0.108736	16
	3.844074	0.124725	18
	4.08032	0.066623	7

Table B.43
Energy GMM — Time cycle: Friday, User profile: Pillow.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.459418	0.153072	3
	0.98009	0.153072	8
	1.440066	0.153072	15
	1.867003	0.153072	15
	1.880221	0.153072	15
	1.907986	0.153072	12
	2.249817	0.153072	16
	2.67536	0.153072	13
	3.16431	0.153072	5
7.4	1.841655	0.373229	12
	2.713952	0.318886	39
	3.319979	0.251892	44
	3.84963	0.085834	4
11	1.944226	0.334096	10
	2.713127	0.256522	27
	3.311677	0.20025	29
	3.717463	0.190291	27
	4.074917	0.083764	8

Table B.44
Energy GMM — Time cycle: Saturday, User profile: Visit.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.114795	0.130674	2
	0.762644	0.28139	19
	1.021784	0.172397	11
	1.310739	0.110342	11
	1.507963	0.088321	11
	1.678319	0.078745	9
	1.863087	0.095668	15
	2.082307	0.179952	19
	2.473955	0.085267	3
7.4	0.842049	0.233704	9
	1.341995	0.219196	15
	1.626041	0.149578	11
	1.918734	0.136727	14
	2.204179	0.145846	14
	2.497131	0.146828	17
	2.900269	0.183332	16

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Table B.44 (*continued*).

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
	3.23686	0.083545	4
11	0.867412	0.17435	3
	1.638786	0.336579	16
	1.973909	0.165251	13
	2.273662	0.121656	11
	2.508683	0.112629	11
	2.735923	0.110794	12
	2.98763	0.13325	13
	3.320488	0.169614	16
	3.652555	0.09405	4

Table B.45
Energy GMM — Time cycle: Saturday, User profile: Shortstay.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	−0.726341	0.26728	8
	−0.128009	0.164711	28
	0.204876	0.125099	31
	0.461121	0.09239	26
	0.630212	0.03714	7
7.4	−0.013155	0.23207	21
	0.58206	0.267002	55
	1.090577	0.12874	18
	1.318374	0.043261	5
11	−0.004336	0.096982	3
	0.644126	0.278886	19
	1.013113	0.105762	16
	1.243309	0.087182	19
	1.425699	0.081989	19
	1.599425	0.074053	17
	1.732376	0.03285	6

Table B.46
Energy GMM — Time cycle: Saturday, User profile: Dinner.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.034847	0.320906	14
	1.617694	0.198014	20
	1.888357	0.103307	27
	2.164843	0.123226	23
	2.511368	0.167668	17
7.4	1.056701	0.268114	4
	2.107717	0.371184	29
	2.454157	0.186885	15
	2.644866	0.146449	15
	2.973002	0.137165	22
	3.254229	0.097775	14
	3.440834	0.021964	2
11	2.000636	0.465901	15
	2.644475	0.312334	31
	3.182168	0.167129	23
	3.494036	0.164168	28
	3.822899	0.061574	4

Table B.47
Energy GMM — Time cycle: Saturday, User profile: Commuters.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.025267	0.259671	11
	1.580413	0.191724	18
	1.837099	0.074549	14
	1.955516	0.083147	13
	2.157455	0.14738	20
	2.436218	0.41192	20
	3.275342	0.178405	5
7.4	1.901668	0.438405	15
	2.718625	0.317922	35
	3.339157	0.244935	41

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Table B.47 (*continued*).

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
	3.898714	0.088503	8
11	2.025392	0.349224	10
	2.957718	0.347203	31
	3.444967	0.189558	29
	3.819524	0.151023	22
	4.085958	0.06918	8

Table B.48
Energy GMM — Time cycle: Saturday, User profile: Home.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.096347	0.34272	16
	1.905975	0.080467	9
	1.959516	0.327516	68
	3.122686	0.303164	7
7.4	0.921478	0.122298	1
	2.029797	0.477369	24
	2.526584	0.147514	13
	2.720309	0.044149	3
	2.922883	0.112149	14
	3.180856	0.107533	15
	3.43581	0.128179	17
	3.832064	0.125952	10
	4.054226	0.056565	3
11	1.854971	0.327311	10
	2.820794	0.364021	25
	3.283425	0.213425	20
	3.623494	0.165	26
	3.941067	0.106657	15
	4.12459	0.050042	5

Table B.49
Energy GMM — Time cycle: Saturday, User profile: Pillow.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.121935	0.382194	15
	1.530458	0.150322	13
	1.860753	0.097405	28
	2.127962	0.128361	20
	2.594168	0.235366	19
	3.274879	0.141824	5
7.4	1.877998	0.329937	12
	2.531936	0.197572	18
	2.870422	0.123704	14
	3.123214	0.10599	15
	3.351387	0.126715	22
	3.669741	0.151555	16
	3.964524	0.046719	3
11	1.996818	0.374863	10
	2.70948	0.203309	20
	3.155823	0.14612	14
	3.417877	0.120693	18
	3.708616	0.137699	23
	3.991117	0.086326	11
	4.141948	0.039333	4

Table B.50
Energy GMM — Time cycle: Sunday, User profile: Visit.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.287138	0.180776	4
	0.908531	0.240202	22
	1.344141	0.171673	16
	1.614415	0.144786	17
	1.867342	0.103707	18
	2.134666	0.176417	19
	2.530853	0.07932	3
7.4	0.967908	0.324782	13
	1.553136	0.22467	20

(*continued on next page*)

Table B.50 (*continued*).

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
	1.988679	0.183407	19
	2.390648	0.169199	19
	2.819623	0.221786	22
	3.23501	0.099427	7
11	0.890052	0.189977	3
	1.759482	0.374495	18
	2.047709	0.196151	12
	2.406005	0.143931	12
	2.653487	0.126449	11
	2.88263	0.13171	12
	3.177365	0.145246	15
	3.512406	0.151286	14
	3.797781	0.063331	2

Table B.51
Energy GMM — Time cycle: Sunday, User profile: Shortstay.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	−0.696297	0.27396	9
	−0.096969	0.159167	31
	0.103193	0.044476	9
	0.263163	0.077811	19
	0.44157	0.081644	24
	0.593843	0.035344	9
7.4	0.012557	0.250587	23
	0.593306	0.259024	55
	1.067954	0.117849	15
	1.268368	0.047501	7
11	−0.049269	0.197528	5
	0.689712	0.316987	19
	1.072166	0.140069	23
	1.382185	0.128812	33
	1.612485	0.068881	13
	1.724512	0.033107	6

Table B.52
Energy GMM — Time cycle: Sunday, User profile: Dinner.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	0.985074	0.312153	14
	1.597075	0.206091	20
	1.868598	0.108346	30
	2.158158	0.159442	28
	2.525912	0.10667	8
7.4	1.32485	0.414834	10
	2.170574	0.298141	36
	2.490403	0.107716	14
	2.811552	0.141826	23
	3.15732	0.121971	15
	3.383804	0.039424	3
11	1.179076	0.168469	2
	2.099464	0.35527	19
	2.586843	0.195213	15
	2.881779	0.134815	9
	3.043332	0.097539	9
	3.190147	0.087319	10
	3.360387	0.102233	16
	3.593798	0.115195	17
	3.823709	0.038277	2

Table B.53
Energy GMM — Time cycle: Sunday, User profile: Commuters.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.042938	0.314879	13
	1.520828	0.122741	10
	1.865159	0.099445	22
	2.099008	0.167535	22
	2.238169	0.439994	29
	3.252299	0.156226	4
7.4	2.045522	0.534484	23
	2.831171	0.315403	33
	3.403564	0.22208	35
	3.885567	0.086892	8
11	1.920705	0.32299	9
	2.792789	0.316224	21
	3.236847	0.176265	15
	3.470178	0.12002	16
	3.718123	0.108391	19
	3.983259	0.092644	16
	4.152795	0.038475	4

(*continued on next page*)

Table B.53 (*continued*).

Table B.54
Energy GMM — Time cycle: Sunday, User profile: Home.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.107553	0.380746	18
	1.570809	0.14135	13
	1.822013	0.066297	12
	1.951138	0.071217	14
	2.147338	0.136034	18
	2.296246	0.394958	22
	3.260426	0.161838	3
7.4	2.039114	0.521925	22
	2.739473	0.314578	28
	3.365529	0.245732	40
	3.975853	0.113088	10
11	1.863179	0.33666	10
	2.889446	0.367012	27
	3.368369	0.188471	22
	3.68393	0.145701	23
	3.975059	0.097962	14
	4.14488	0.043603	5

Table B.55
Energy GMM — Time cycle: Sunday, User profile: Pillow.

Charging rate (kW)	Mean (μ)	Std. deviation (σ)	Share (%)
3.7	1.118632	0.412432	17
	1.575953	0.191332	17
	1.814923	0.064828	11
	1.932111	0.073806	14
	2.130719	0.115457	17
	2.544329	0.256278	19
	3.262032	0.137752	4
7.4	1.929276	0.463627	16
	2.769087	0.330794	37
	3.360976	0.246669	43
	3.894336	0.076859	4
11	2.052186	0.430069	13
	2.697816	0.195298	16
	3.087522	0.129339	10
	3.296396	0.097109	11
	3.487852	0.090815	13
	3.699953	0.109732	17
	3.973843	0.104073	15
	4.157585	0.047094	4

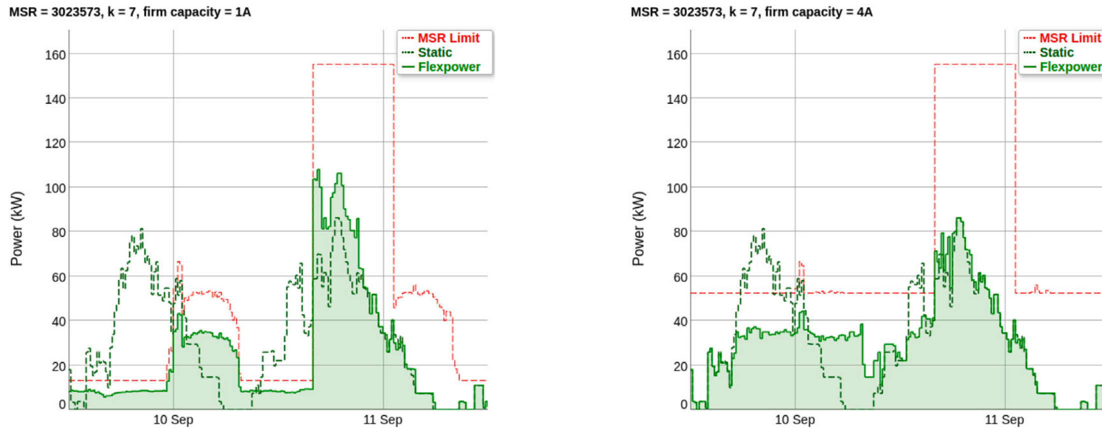

Fig. C.1. MSR 3023573 with $k = 7$, comparing $FirmCapacity = 1$ (left) and $FirmCapacity = 4$ (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

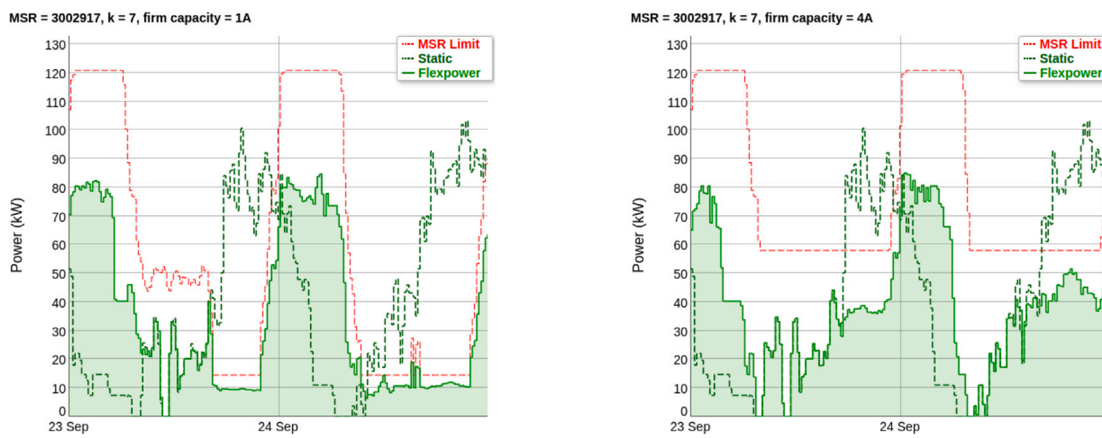

Fig. C.2. MSR 3002917 with $k = 7$, comparing $FirmCapacity = 1$ (left) and $FirmCapacity = 4$ (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

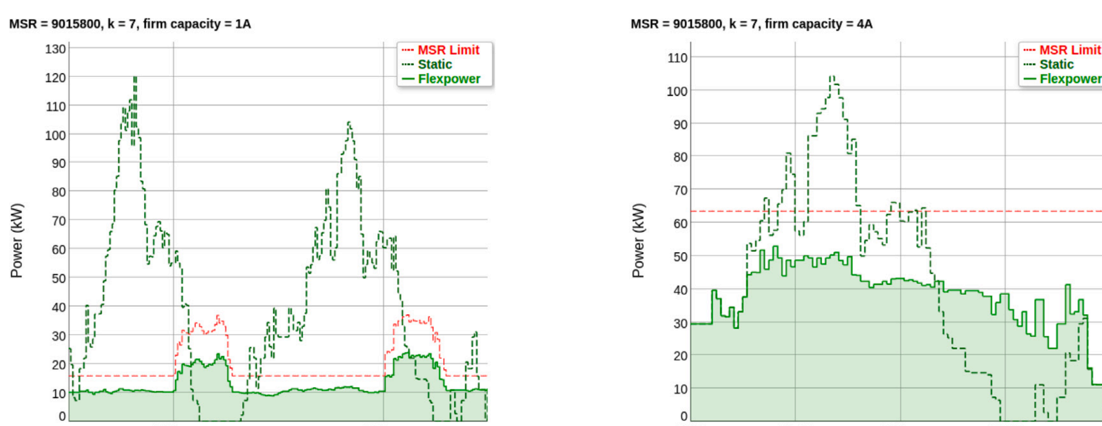

Fig. C.3. MSR 9015800 with $k = 7$, comparing $FirmCapacity = 1$ (left) and $FirmCapacity = 4$ (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix C. Flexpower simulations

This appendix shows some examples of the Flexpower simulations, concerning different MSR, EV penetration scenarios (k) and firm capacity values. The MSR limits set by the DSO are represented in red dashed lines, the static EV demand in green dashed lines, and the Flexpower EV demand in green shaded lines.

Appendix D. Summary tables of results

This appendix contains the coloured tables with the average indicators described in Section 5.5. The six figures represent future EV penetration scenarios in a range of $k \in [2, 7]$.

Firm capacity (A)	Uncompleted sessions (%)	Demand peak reduction (%)	Total energy charged (%)	Avg. energy charged (%)
1	33	93	81	80
2	26	86	88	87
3	20	80	93	92
4	14	75	96	95
5	10	67	98	97
6	7	62	99	98
7	4	55	99	99
8	3	49	100	100

Fig. D.1. Summary of results from EV penetration scenario $k = 2$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Firm capacity (A)	Uncompleted sessions (%)	Demand peak reduction (%)	Total energy charged (%)	Avg. energy charged (%)
1	40	94	80	75
2	32	87	87	83
3	25	80	91	89
4	19	75	95	93
5	14	69	97	95
6	10	62	98	97
7	6	55	99	99
8	4	50	99	99

Fig. D.2. Summary of results from EV penetration scenario $k = 3$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Firm capacity (A)	Uncompleted sessions (%)	Demand peak reduction (%)	Total energy charged (%)	Avg. energy charged (%)
1	45	93	79	72
2	37	87	84	80
3	28	80	91	87
4	21	74	95	91
5	14	66	97	95
6	10	59	98	97
7	6	53	99	99
8	3	46	100	100

Fig. D.3. Summary of results from EV penetration scenario $k = 4$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Firm capacity (A)	Uncompleted sessions (%)	Demand peak reduction (%)	Total energy charged (%)	Avg. energy charged (%)
1	49	94	76	69
2	40	87	78	78
3	31	81	89	85
4	22	74	94	90
5	16	68	97	94
6	11	61	98	97
7	6	54	99	99
8	4	47	100	99

Fig. D.4. Summary of results from EV penetration scenario $k = 5$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Firm capacity (A)	Uncompleted sessions (%)	Demand peak reduction (%)	Total energy charged (%)	Avg. energy charged (%)
1	54	93	67	66
2	44	87	76	76
3	33	80	87	84
4	23	73	94	91
5	15	66	97	95
6	9	59	99	98
7	6	52	99	99
8	5	46	100	99

Fig. D.5. Summary of results from EV penetration scenario $k = 6$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Firm capacity (A)	Uncompleted sessions (%)	Demand peak reduction (%)	Total energy charged (%)	Avg. energy charged (%)
1	58	93	62	63
2	48	86	71	73
3	36	79	86	83
4	25	72	94	90
5	13	65	97	95
6	9	57	98	97
7	8	54	99	98
8	7	48	99	98

Fig. D.6. Summary of results from EV penetration scenario $k = 7$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Data availability

The authors do not have permission to share data.

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