MODELLING OF ELECTRIC VEHICLE USER PROFILES FOR FLEXIBILITY MANAGEMENT AND CHARGING INFRASTRUCTURE PLANNING

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Universitat de Girona

PhD Thesis

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DOCTORAL THESIS

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DOCTORAL PROGRAM in TECHNOLOGY

Supervised by:
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Moreover, during the development of this thesis, the candidate has contributed to other results that complement the work in the compendium. Contributing publications derived from those results are listed below:

Conferences

- Cañigueral, M., & Meléndez, J. (2021). Electric vehicle user profiles for aggregated flexibility planning. In 2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe). IEEE.
- Cañigueral, M., & Meléndez, J. (2023). A prediction tool to evaluate EV charging demand based on socio-demographic indicators. In CIRED 2023 International Conference & Exhibition on Electricity Distribution.

Workshops

- Cañigueral, M., & Meléndez, J. (2022). Potential benefits of scheduling electric vehicle sessions over limiting charging power. In CIRED Porto Workshop 2022: E-mobility and power distribution systems. Institution of Engineering and Technology.

Acronyms

BIC Bayesian Information Criterion
BRP Balance Responsible Party
CPO Charging Point Operator
DBSCAN Density-Based Spatial Clustering of Applications with Noise
DER Distributed Energy Resources
DSO Distribution System Operator
EM Expectation-Maximization
EU European Union
EV Electric Vehicle
GMM Gaussian Mixture Models
MM Mixture Models
MSR Middenspanningsruimte (Low-voltage transformer in Dutch)
PDF Probability Density Function
PV Photovoltaic
RES Renewable Energy Sources
TSO Transport System Operator
USEF Universal Smart Energy Framework

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Abstract

The transition to electric mobility is facing multiple challenges, usually associated with the roll-out of the charging infrastructure. On one hand, cities must develop a charging infrastructure that meets the user needs while the type of electric vehicle (EV) users is specific for every charging area. On the other hand, a high EV demand in the power system can bring congestion issues at the low-voltage power grid and this can involve power supply quality issues and a barrier to further development of the charging infrastructure. This thesis aims to provide tools to solve the challenges raised in both stages of the adoption of electric mobility. With this purpose, a methodology to cluster and model generic EV user profiles based on connection patterns is proposed and applied to these two key areas: flexibility management and charging infrastructure planning.

The concept of user profiles is introduced as a tool to identify common connection patterns with a characteristic flexibility potential. A clustering methodology using Gaussian Mixture Models (GMM) is applied based on variables such as connection start time and duration. Common usage patterns in public charging infrastructure are observed, providing insights into EV user behaviour. The profiling methodology is validated with three different real data sets of charging sessions along with the three journal articles that shape the core of this thesis.

The clustering methodology is followed by a modelling methodology to perform stochastic simulations of EV charging sessions in terms of connection times, required energy and charging power rate. Modelling every user profile independently lets to simulate a wide range of scenarios since the share of each user profile over the total EV demand can be configured according to the environment (i.e. location, time horizon, etc.). This application is explored with two journal articles where scenarios with high penetration of EV sessions are simulated to (1) optimally size a charging hub and (2) analyse the required number of charging points of city-level charging infrastructure. In both contributions, the configuration of user profiles in specific areas is crucial for properly sizing charging infrastructure, avoiding extra costs that harm the business model or losing EV users' confidence with undersized installations.

This thesis also compares different smart charging strategies through simulations, as well as the benefits that the user-profile approach could bring to smart charging programs. When scheduling individual sessions according to an aggregated demand setpoint, the extra knowledge of profiling EV users beforehand can provide insights for a more reliable flexibility prediction. Moreover, scheduling sessions from selected user profiles could lead to exploitation cost savings and reduced impact on EV users.

Finally, the application of a smart charging program at the city level with high penetration of EVs has been also simulated to analyse its impact on all stakeholders involved in the EV charging sector, from the final EV user to the charging operator business model. Curtailing charging power based on dynamic capacity signals proves effective to avoid grid congestion and defer reinforcements of the existing power grid while expanding the charging infrastructure and supplying the majority of the energy required by EV users.

Overall, this thesis enhances understanding of EV user behaviour, analyses different smart charging strategies, and provides insights for charging infrastructure planning. These findings have practical implications for stakeholders involved in the EV ecosystem, contributing to the ongoing transition to electric mobility.

Resum

La transició a la mobilitat elèctrica s'enfronta a múltiples reptes, generalment associats amb el desplegament de la infraestructura de càrrega. D'una banda, les ciutats han de desenvolupar una infraestructura de càrrega que satisfaci les necessitats dels usuaris, mentre que el tipus d'usuaris de vehicles elèctrics (VE) són específics per a cada àrea de càrrega. D'altra banda, una alta demanda de VE en el sistema d'energia pot portar problemes de congestió a la xarxa elèctrica de baixa tensió i això pot implicar problemes en la qualitat del subministrament elèctric i una barrera per a un major desenvolupament de la infraestructura de càrrega. Aquesta tesi pretén proporcionar eines per resoldre els reptes plantejats en les dues etapes de l'adopció de la mobilitat elèctrica. Amb aquest objectiu, es proposa una metodologia per agrupar i modelar perfils d'usuari genèrics de VEs basats en patrons de connexió, la qual s'aplica en dues àrees clau: gestió de la flexibilitat i planificació d'infraestructures de càrrega.

El concepte de perfils d'usuari s'introdueix com una eina per identificar patrons de connexió comuns amb un potencial de flexibilitat característic. Una metodologia d'agrupament que utilitza Models Mixtos Gaussians (MMG) s'aplica basant-se en variables com l'hora d'inici i la durada de la connexió. S'observen patrons d'ús comuns en la infraestructura de càrrega pública, proporcionant informació sobre el comportament dels usuaris de VEs. La metodologia d'elaboració de perfils es valida amb tres conjunts de dades reals de sessions de càrrega juntament amb els tres articles de revista que configuren el nucli d'aquesta tesi.

La metodologia d'agrupació és seguida per una metodologia de modelatge per realitzar simulacions estocàstiques de les sessions de càrrega del VE en termes de temps de connexió, energia requerida i potència de càrrega. Modelar cada perfil d'usuari independentment permet simular una àmplia gamma d'escenaris, ja que la presència de cada perfil d'usuari sobre la demanda total del VE es pot configurar segons l'entorn, és a dir, la ubicació, l'horitzó temporal, etc. Aquesta aplicació s'explora amb dos articles de revista on es simulen escenaris amb alta penetració de sessions de VE per (1) dimensionar de manera òptima una àrea de càrrega i (2) analitzar el nombre requerit de punts de càrrega a nivell de ciutat. En ambdues contribucions, la configuració de perfils d'usuari en àrees específiques és crucial per

un dimensionament adequat de la infraestructura de càrrega, evitant costos addicionals que perjudiquin el model de negoci o la pèrdua de confiança dels usuaris del VE amb instal · lacions sotadimensionades.

Aquesta tesi també compara diferents estratègies de càrrega intel · ligent a través de simulacions, així com els beneficis que l'enfocament de perfilat d'usuaris podria aportar als programes de càrrega intel · ligents. Quan es programen sessions individuals d'acord amb una consigna de demanda agregada, el coneixement addicional de perfils de VE poden proporcionar informació per a una predicció de flexibilitat més fiable. A més, les sessions de programació dels perfils seleccionats podrien conduir a un estalvi de costos d'explotació i a una reducció de l'impacte sobre els usuaris de VEs.

Finalment, l'aplicació d'un programa de càrrega intel · ligent a nivell de ciutat amb alta penetració de VEs també s'ha simulat per analitzar el seu impacte en totes les parts interessades implicades en el sector de càrrega del VE, des de l'usuari final fins al model de negoci del gestor de càrrega. Una limitació de la potència de càrrega basada en senyals de capacitat dinàmica resulta eficaç per evitar la congestió de la xarxa i ajornar millores en la xarxa elèctrica existent mentre s'expandeix la infraestructura de càrrega i es subministra la majoria de l'energia requerida pels usuaris de VEs.

En general, aquesta tesi millora la comprensió del comportament de l'usuari de VE, analitza diferents estratègies de càrrega intel · ligents i proporciona informació per a la planificació de la infraestructura de càrrega. Aquests resultats tenen implicacions pràctiques per a les parts implicades en l'ecosistema del VE, contribuint a la transició cap a la mobilitat elèctrica.

Chapter 1

Introduction

Electric vehicles (EVs) are seen as the opportunity to increase the efficiency of the mobility sector and decrease greenhouse gas emissions, air pollution and urban noise in cities. Thus, the adoption of EVs is on the roadmap of all European countries, increasing the share of EVs over the total transportation fleet with 2 million vehicles sold in the first quarter of 2022 [1]. However, several challenges arise in the different stages of this transition, mainly related to the deployment of the charging infrastructure. This thesis aims to contribute to solving some of these challenges by providing a methodology to identify and model different profiles of EV users for analysing the present and future of EV demand.

1.1 Motivation

One of the major barriers for citizens to shift to electric mobility is the lack of proper charging infrastructure, especially in urban areas or regions with high-density populations [2]. Since most citizens still have questions and concerns about the future of electric mobility, the system must accomplish the objective of convincing them that it is prepared for this transition. The trust of EV users in the charging infrastructure and their acceptance as a reliable service is a key enabling factor of this transition, like any other new business model [32]. An example of this is that initial investments in charging infrastructure, from public or private entities, have an immediate positive effect on EV adoption [17]. Thus, it is clear that the charging infrastructure must have progressive growth, but the focus should not only be the quantity of charging areas, the density of charging points or the expected daily users. It also matters about the “when” and “where”, since the distribution of EV users over the day will define whether the charging infrastructure is properly sized or not.

Therefore, it is crucial to know the typology of the expected EV demand when planning a new charging infrastructure or expanding an existing one. The public charging infrastructure must be deployed considering both the environment in which it is deployed and the behaviour patterns of EV users to enable large-scale adoption of EVs [21]. This is an important point, given that the EV demand can be very different from city to city but also from district to district. For this reason, this thesis aims to develop a modelling methodology from a user-profile approach, identifying characteristic EV user profiles to simulate the corresponding combination of these patterns according to the use case.

On the other hand, in places where the charging infrastructure has been deployed successfully, the EV demand together with the electrification of other sectors such as climatization (e.g. air-conditioning or heat pumps), is resulting in more accentuated demand peaks, mostly in low-voltage distribution grids and at substation level [24], and a stronger mismatch between demand and renewable (e.g. solar) production. Currently, vehicles start charging instantaneously at connection time and most users connect the vehicles at the workplace or at home [23], coinciding with the traditional peak demand in the morning and the evening. This could result in an efficiency reduction of the overall power system (e.g. backup generation, an increase of thermal losses, etc.) and the corresponding increase of grid operation complexity (e.g. congestion management, frequency regulation, voltage control, etc.).

However, the EV could also be part of the solution to this scenario if the power system makes use of the flexibility potential of their individual batteries as distributed storage resources. Flexibility is defined in this context as the capability of an energy asset (e.g. loads, generators, storage elements, prosumers, etc.) to temporarily modify its demand profile without affecting the service it provides to the end user. The flexibility of a single vehicle is small, but the aggregated impact of a fleet or the management of large charging infrastructures (e.g. public charging stations) can be significant and of special interest to Distribution System Operators (DSO), Transport System Operators (TSO) or Balance Responsible Parties (BRP) in order to support congestion management at specific geographic locations [27]. Usually, two main approaches are described to lever the participation of these distributed flexible resources: implicit and explicit demand-side flexibility [26].

In the implicit approach, prosumers are exposed to variable energy prices or grid access tariffs (e.g. Time of use tariffs), while in the explicit flexibility approach, the power demand is controlled in order to adjust the load curve in size, location and time. This control can be motivated by a direct bilateral agreement between the system operators (DSO, TSO or BRP) and the flexibility providers such as Charging Point Operators (CPO), or through a flexibility market and the figure of a flexibility aggregator. Thus, an aggregator could be a new market player together with other parties already active in the EV sector, such as parking or fleet owners, CPOs or e-mobility service providers. In that sense, USEF [26] is a foundation with the goal to establish an integrated smart energy system and has also been working on the definition of the electric vehicles' flexibility environment. As a result of their work, Figure 1.1 shows all possible combinations of flexibility requesters (DSO, TSO, BRP), objectives (self-balancing, congestion management, etc.) and parties (aggregators, CPO, car manufacturers, etc.).

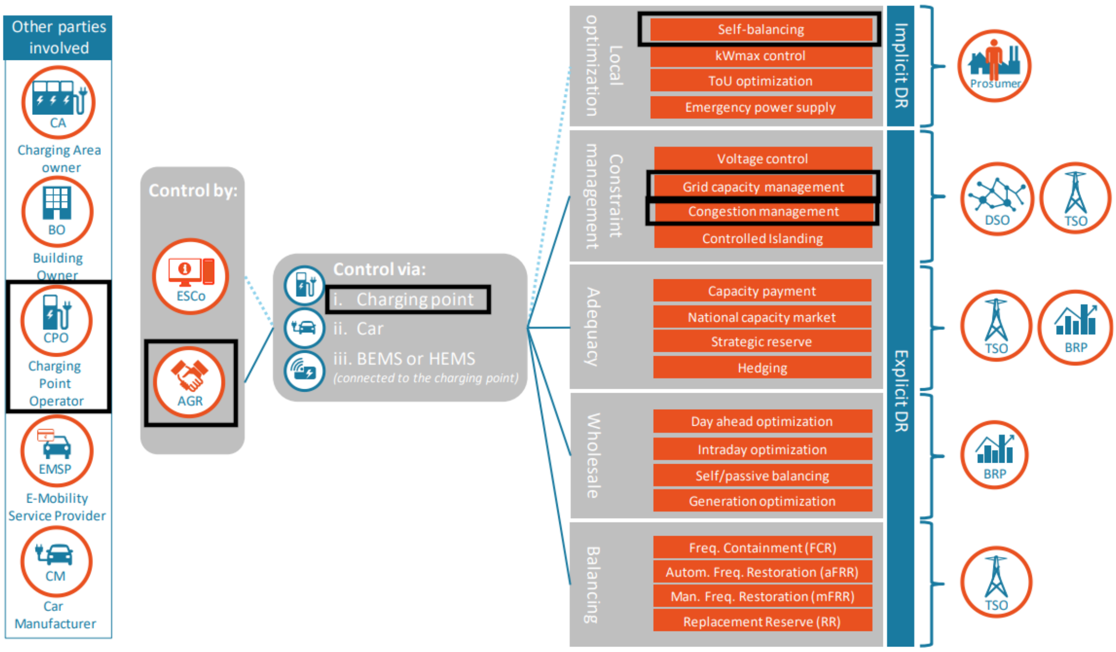

Figure 1.1: EV smart charging landscape with highlighted contribution fields in this thesis. Original image from USEF [25]

The original USEF figure has been modified by highlighting the fields to which this thesis contributes, focusing on the scenario where the CPO controls the public charging infrastructure to provide services to the DSO (grid capacity and congestion management, see Chapter 5) or local energy communities (self-balancing, see Chapter 3). In this scenario where the CPO has to control the charging points, the risk of impacting the EV users' charge is a relevant factor to take into account. The EV users will lose trust and confidence in the charging system if they can connect the vehicle but the vehicle does not charge either because the grid is congested and it cannot supply any additional load, or the charging point is being operated (e.g. switched off, power limitation, etc.) as a consequence of its participation in a demand response program. Therefore, the limitation of charging sessions that are actually not flexible can suppose a negative effect on user acceptance. However, most of the current literature applies a single smart charging objective (e.g. peak shaving) to all charging sessions connected to the infrastructure without taking care of the individual sessions' flexibility potential or preferences. For this reason, this thesis aims to provide the aggregators or CPOs with this information through a clustering methodology to classify EV sessions into user profiles, representing characteristic connection patterns and the corresponding flexibility potential. The utilization of this extra knowledge about the flexibility of EV users could reduce the uncertainty in the flexibility potential of the aggregated EV demand, improve the performance of smart charging programs by reducing exploitation costs (fewer exploited sessions), and lower the impact on the final EV user.

1.2 Objectives

The global goal of this thesis is to pave the way for the adoption of electric vehicles by providing methods and tools to increase knowledge about EV demand, support the charging infrastructure planning and assess the benefits of managing EV flexibility for the power system. The main hypothesis is that understanding user behaviour and preferences is crucial for effective planning and optimization of charging infrastructure and energy management systems. Thus, in order to validate this hypothesis the following objectives have been fixed:

- O1 Given a real data set of charging sessions, discover and identify EV user profiles with a representative connection patterns and assess their flexibility potential.

- O2 Model EV user profiles to perform stochastic simulations of EV demand in a wide range of scenarios, considering different amounts of charging sessions but also the presence of user profiles according to the use case.

- O3 Analyse the impact and opportunities of managing the flexibility of charging sessions by applying different control strategies, assessing the added value of profiling EV users.

1.3 Background and related work

This section introduces the required background and a general state-of-the-art in the research areas of this thesis: clustering and modelling of EV user profiles and flexibility management of EVs.

A more specific state-of-the-art can be found in each one of the journal publications included in Chapters 3, 4 and 5.

1.3.1 Clustering and modelling of EV user profiles for stochastic simulations

The first objective of this thesis is to identify generic user profiles from real data sets of EV charging sessions. In this work, the concept of 'user profile' is understood as a daily connection pattern defined by the connection start and end times. Several works have studied how to detect EV patterns according to the daily habits of owners.

The energy charged per session was used as a discriminatory variable in [14], differentiating between locals and visitors from a certain threshold. A classification between users charging at the workplace, at home or parking-to-charge is done in [23] using DBSCAN clustering to discover the different groups, considering as clustering variables the connection start and end times. Similarly, office chargers, home chargers and visitors are differentiated in [6] using a heat map and specific thresholds of connection start time and connection duration variables. In contrast, a multinomial logistic regression technique over a single variable (i.e. connection duration) was used in [29] to classify sessions between stop&charge, park&charge, work&charge, home&charge and long sessions. A four-variable (session start time, connection duration, hours between sessions and distance between sessions) Gaussian Mixture Model (GMM) was used in [16] as a clustering method to discover three types of office hours users, three types of overnight users and three types of non-typical users.

In summary, a wide variety of clustering methods and a number of variables are used in this research field, from a single-variable threshold classification to Mixture Models (MM) of 4 variables. However, threshold classifications may lack user information, while using variables like the distance driven may require too much information from EV users. Therefore, a bivariate Gaussian Mixture Model clustering is proposed as a robust classification method, general enough to be applied to any other data set since it relies upon the two basic variables that define the EV user behaviour: connection start time and duration.

A disadvantage of GMM clustering is that it requires to pre-define the number of clusters. A common solution to overcome this is the Bayesian Information Criterion (BIC) to find the optimal number of clusters, which adds a penalty to the loglikelihood based on the number of parameters [11].

$$\mathrm{BIC} = 2\mathrm{loglik}_{\mathcal{M}}(x, \theta_k^*) - (\#\mathrm{params})_{\mathcal{M}} \log(n) \tag{1.1}$$

where $\mathrm{loglik}_{\mathcal{M}}(x, \theta_k^*)$ is the maximized loglikelihood for the model, $(\#\mathrm{params})_{\mathcal{M}}$ is the number of independent parameters to be estimated in the model $\mathcal{M}$, and n is the number of observations in the data.

The BIC algorithm not only takes into account the number of clusters but also the parameterization of the covariance matrix, which can be defined in multiple ways as shown in Table 1.1.

identifier	Distribution	Volume	Shape	Orientation
E	(univariate)	equal		
V	(univariate)	equal		
EII	Spherical	equal	equal	NA
VII	Spherical	variable	equal	NA
EEI	Diagonal	equal	equal	coordinate axes
VEI	Diagonal	variable	equal	coordinate axes
EVI	Diagonal	equal	variable	coordinate axes
VVI	Diagonal	variable	variable	coordinate axes
EEE	Ellipsoidal	equal	equal	equal
EEV	Ellipsoidal	equal	equal	variable
VEV	Ellipsoidal	variable	equal	variable
VEV	Ellipsoidal	variable	variable	variable

Table 1.1: Parameterizations of the covariance matrix for EM for multidimensional data. Source: mclust 4 [11]

On the other hand, an advantage of GMM in contrast to other clustering methods like DBSCAN or heat maps is that it is robust to the uncertainty associated with EV user behaviour. This is an important point given all factors that can influence our daily connection patterns. Thus, the capability of Mixture Models (MM) to model complex distributions [20] make them an appropriate method to capture the stochasticity in charging demand. This feature gives a direct advantage to GMM in comparison to other clustering methods since the statistic parameters of the models are directly obtained in the clustering process, avoiding further processing and modelling of clusters identified by non-parametric methods [30]. Other works in the current literature model the EV demand with Probability Density Functions (PDF) to include stochasticity in the simulation [22, 31]. However, these PDF models do not represent the multiple EV user behaviours present in a specific use case, and it is difficult to define the accuracy of the simulation when extrapolating these models to other environments.

To solve this problem, this thesis proposes a modelling methodology to model EV user profiles based on MM to capture the stochasticity of the EV demand. If the EV user profiles discovered from a data set can be equivalent to behaviour of citizens from other use cases (e.g. other cities), their models can be used to simulate the corresponding EV demand. Moreover, given that the models of every user profile are independent of each other, a wide range of environments can be simulated since the number of charging sessions from every user profile can be defined in order to match the characteristics of specific charging area (e.g. city centre, residential neighbourhood, industrial area, etc.).

1.3.2 Flexibility management of electric vehicles

By strategically controlling the charging patterns of EVs, it is possible to address key challenges faced by the power system, such as integrating intermittent renewable energy sources, managing peak demand and even providing ancillary services to support the grid. However, to modify the power profile of charging sessions, first it is necessary to define the corresponding flexibility potential and how this flexibility is exploited.

Electric vehicles' charging sessions are characterized by connection start and end times (i.e. a certain connection duration time) and energy that has been charged (until filling the battery or disconnecting the vehicle). In a simplified business-as-usual charging model [28], represented in Figure 1.2, the constant charging power together with the charged energy determine the charging time. This is a simplified model since real charging power normally decreases when the battery is nearly full [12]. Given this simplified model, the flexibility that an electric vehicle could provide can be defined in multiple dimensions:

- Time: the time periods when the vehicle charges can be variable while the vehicle remains connected.
- Energy: the user could accept to charge less energy, or the vehicle could be discharged in V2G systems.
- Power: the charging power can be reduced (increasing the charging time), increased (if allowed by the vehicle) or even negative if the vehicle is discharged in V2G systems.

At the same time, these different flexibility dimensions allow us to also define different smart charging control strategies [28]:

- Postpone: shifting the charging time along the connection time
- Curtail: reduce charging power
- Interrupt: stop charging the vehicle during some period of time
- V2G: discharge the vehicle along the connection time
- Combination of multiple strategies above

Figure 1.2 also illustrates the two strategies considered in this thesis, postpone and curtail, in the first (see Chapter 3) and third (see Chapter 5) articles of this compendium, respectively. The algorithms developed for the simulation of these control strategies are described in Chapter 2, which focuses on describing the methodological aspects developed in the thesis.

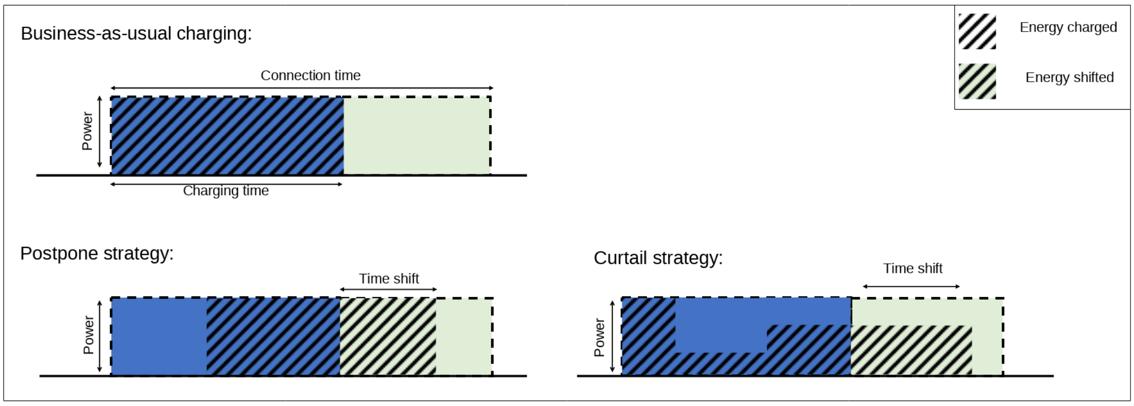

Figure 1.2: Charging control strategies presented in this thesis

Beyond the control strategy chosen, other decisions must be made during the design process of the smart charging architecture. As mentioned at the beginning of this Introduction chapter, this thesis is focused on delivering flexibility to avoid congestion problems in the low-voltage power grid, focusing on the control of public charging points managed by the CPO according to grid capacity signals from the DSO. Within this scheme illustrated by Figure 1.3, the design of the system must address the following aspects:

Capacity signals:

- Static (e.g. fixed thresholds according to date/time) or dynamic (e.g. power profile defined according to solar generation forecast)
- Time resolution of the power capacity profile (e.g. 15-minute power profile)
- Agreement type (e.g. bilateral communication with the system operator, auction in flexibility market, etc.)

Charging control:

- Strategy of the control (e.g. postpone, curtail, interrupt, etc.)
- Capacity share (e.g. all sessions treated equally, preference or prioritisation system, etc.)

User interaction:

- Override option to skip smart charging (e.g. smartphone app, charging point interface, etc.)
- Rewarding mechanism (e.g. money discount, cheaper tariff, etc.)

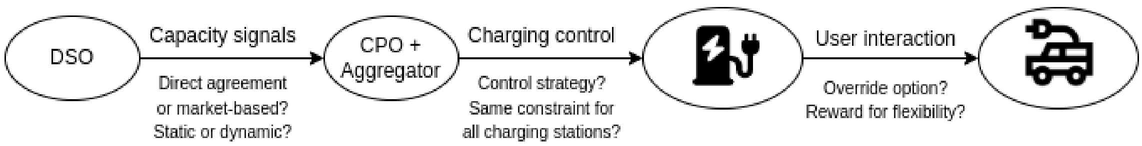

Figure 1.3: Charging control strategies presented in this thesis

Different combinations of this scheme have been already tested within EU pilot projects during the last few years. An example of a successful pilot is the Flexpower project in Amsterdam [5], where the amperes per phase of all charging stations in the pilot were limited (curtail strategy) during peak hours but increased during the rest of the day (static signal). Another pilot that implemented a static power profile limitation was carried out by the Dutch DSO Enexis [4], using domestic charging points in this case, also reducing the maximum charging power during peak hours. However, both Dutch pilots experienced some drawbacks such as a rebound effect, increasing the peak demand after the activation of flexibility measures by shifting energy from the constrained to the unconstrained time period.

Even though a rebound is not a problem during demand valley hours, it could be significant if not properly controlled. It is necessary to explore the opportunities of reducing rebound peaks, for example by designing a more gradual increase in charging speed after the off-peak limit [5] or applying dynamic control with feedback from real-time monitoring. With this objective, the Enexis pilot [4] also proposed a dynamic control signal to reduce the charging power according to an aggregator signal. In this scenario, the rebound effect is completely avoided since the increase in demand is continuously corrected thanks to real-time measures.

Other EU projects such as INVADE [33], the third phase of Flexpower [34], or Interflex [13], have also applied dynamic capacity signals, with direct communication with the DSO in the case of INVADE and Flexpower3 and through a flexibility market in case of Interflex. In both projects, the reduction of power depends on the free capacity of the grid, considering also the local PV power and households' demand.

In the INVADE pilot, all charging points were treated equally, so once the dynamic power profile is adjusted, it is used for all active sessions. However, it does not mean it is an equalitarian treatment. If the EV user can not choose whether to participate or not in the smart charging program, the impact of reducing the charging power is higher for a user that is only connected for 3 hours than another that will remain connected the whole night. This could suppose an impact on the users' charging service, especially during a month with high domestic consumption when the share of exploited sessions reached up to 77% [33]. In the same way, Flexpower3 also applies the power constraint to all charging EVs. In contrast, the users participating in the Interflex project needed to actively choose whether to participate, receiving a financial reward in exchange for their flexibility. However, upscaling the reward system from Interflex at the city level like the INVADE or Flexpower3 approaches could make the business model more difficult since the exploitation costs would be too high if the flexibility offered is not paid enough, and if the reward is not relevant for users they would not provide their flexibility.

Finally, another important aspect to take into account when studying the flexibility management of EVs is the location where flexibility is required. The real impact of distributed renewable energy sources (RES) and EVs is in the low-voltage grid and this impact is diverse depending on the location and time. At the same time though, the low-voltage infrastructure has normally a low degree of instrumentation and operated capacity. So, it is necessary to develop strategies to forecast possible critical events and react accordingly. For that purpose, user modelling and simulation permits forecasting the occurrence of these congestion scenarios and evaluating the proposed mitigation actions. Therefore, in contrast to other smart charging studies based on mitigating the impact at the transmission level [15, 18, 3, 10] projects like Flexpower3 [34] put the emphasis on defining dynamic grid capacity signals in order to control congestions at the local level in the low-voltage transformers.

Therefore, it is necessary to use a dynamic control signal to avoid a rebound effect during off-peak hours and exploit only the most flexible sessions to ensure (1) a high quality of service to all users (i.e. both long and short sessions should have time to charge the EV) and (2) a high efficiency of the demand-response program (i.e. lower exploitation costs).

In order to perform this selection of “the most flexible sessions”, there are multiple options. First, the most direct way would be to ask for information to EV users, like the required energy to charge or the expected connection duration or disconnection time. However, this may suppose extra investment in communication infrastructure (e.g. interface, app, servers, etc.) and it requires a certain effort from the user. Second, if the CPO knows the vehicle ID, it could be possible to create a prediction model about these variables based on the historic records of the vehicle. However, this could suppose a challenge in terms of privacy issues for the EV user since this would require using individual data. In that sense, the user-profile approach presented by this thesis could allow the CPO to classify EV users into a certain user profile beforehand and make use of just this information in order to decide whether to postpone a charging session or not. With this extra knowledge, the number of sessions required for reaching the desired impact can be lower (and the corresponding exploitation costs) and the system is scalable with a minimum impact on both the user and the business model.

1.4 Contributions

This thesis aims to provide valuable insights for enhancing the overall EV ecosystem by uncovering underlying patterns among EV users. Given the objectives of the thesis, the contributions of this work fall into three different areas:

- C1 A data-driven methodology for clustering EV user profiles. This methodology provides the tools to classify real EV charging sessions into user profiles that represent daily EV connection patterns. The validated methodology extends the current state of the art in three major aspects:
  - C1.1 A model-based clustering approach based on GMM to capture the stochasticity present in the EV user behaviour
  - C1.2 Custom data preprocessing tools to improve the performance of GMM by:
    - C1.2.1 Dividing data by sub-sets with different user behaviour between them (e.g. working day vs weekend, day sessions vs overnight sessions)
    - C1.2.2 Cleaning method based on density-based clustering DBSCAN
  - C1.3 A two-step profiling method to group clusters under a more high-level label (i.e. user profile name) according to their centroid and variance
- C2 A modelling methodology to simulate EV user profiles in diverse environments. The clustered user profiles must be modelled to enable stochastic simulations of different EV demand scenarios and the corresponding impact analysis. The specific contributions of this methodology in the current state-of-the-art are:
  - C2.1 Stochastic models convenient to simulate the randomness of the EV demand on a daily basis
  - C2.2 Characteristic energy models per user profile but also per charging rate
  - C2.3 Machine learning model to estimate the presence of every EV user profile in a geographic area according to socio-demographic variables
- C3 Algorithms to simulate flexibility management programs with multiple control strategies:

- C3.1 Quadratic optimization algorithm to minimize the energy exchanged with the grid (considering local generation) and the power peaks (flattest demand curve)
- C3.2 Algorithm to postpone individual charging sessions to achieve the optimal aggregated demand setpoint
- C3.3 Algorithm to limit the connection time of individual charging sessions as a regulation measure
- C3.4 Algorithm to limit charging power of individual charging sessions according to dynamic grid capacity signals

These contributions are properly addressed in the different articles from Chapters 3, 4 and 5. Moreover, the methodology together with the algorithms developed has been collected into three open-source R packages (see logos at Figure 1.4) available from Github, each one with its own website with documentation, tutorials and functions reference:

- `evprof`: Electric Vehicle Charging Sessions Profiling and Modelling [7].
- `evsim`: Electric Vehicle Charging Sessions Simulation [8]
- `flextools`: Tools for demand-response optimization [9].

Figure 1.4: Logos from the three R packages developed

1.4.1 Journal Contributions

The multiple objectives of this thesis have been achieved and reported in three journal papers that constitute the core of this thesis.

The first journal paper, presented in Chapter 3, focuses on objectives O1 and O3. The objective O1 is achieved by presenting a clustering methodology based on bivariate Gaussian Mixture Models, which is validated with the Arnhem data set, representing the contributions C1.1 and C1.2.1. The second part of this paper contributes to objective O3 by proposing an algorithm to postpone individual charging sessions (contribution C3.2) according to an aggregated setpoint calculated with a quadratic optimization (contribution C3.1). The charging sessions are coordinated in two different smart charging scenarios, first postponing all required sessions and second coordinating only the sessions belonging to two selected user profiles with high flexibility potential. The second smart charging scenario (i.e. user-profile approach) resulted in more efficient scheduling, obtaining similar peak shaving results than the first scenario with a 35% fewer sessions postponed. These results demonstrate a reduction in exploitation costs of the smart charging scenario and therefore the response to research question Q3.

The second journal paper, presented in Chapter 4, extends through objectives O1-O3 and reports new validation results and improvements in the methodology. First, the clustering methodology presented in Chapter 2 is applied to a Norwegian data set. In this work, the user profiles are used to simulate future scenarios with higher EV demand, so a modelling methodology based on bivariate Gaussian Mixture Models is presented (contribution C2.1). Moreover, the R packages `evprof` and `evsim` to model and simulate EV demand based on user profiles are also presented in this paper. The flexibility management of EVs in this paper (objective O3) is represented by a regulation of the connection time in the charging hub (contribution C3.3), where users have to disconnect the vehicles after a certain period of time.

The third journal paper, presented in Chapter 5, extends through objectives O1-O3. First, the clustering methodology presented in Chapter 3 is applied to the Amsterdam data set, and the modelling methodology presented in Chapter 4 is improved by introducing different energy models for the multiple charging power rates existing in the data set (contribution C2.2). These improvements are also included in the `evprof` package. The EV models are used in this work to simulate a high penetration of EVs in Amsterdam and analyse how the public charging infrastructure should grow. The user-profile modelling approach is essential in this work since the EV demand profile between sub-stations in Amsterdam shows large differences, contributing to anwer research question Q2. The flexibility management of EVs in this paper (objective O3) is represented by a limitation of power in the public charging stations according to the substation dynamic capacity signals set by the DSO (contribution C3.4).

Not included in the core part of this compendium but also related to the objectives of the thesis, three conference publications are presented:

- In the 2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe): contributing to objective O1, the clustering methodology is improved by introducing methods for outliers cleaning based on DBSCAN density-based clustering (contribution C1.2.2).

- In the 2022 CIRED Workshop about E-mobility and power distribution systems: contributing to objective O3, the user profiles were used to show the potential benefits of scheduling pre-selected EV users instead of limiting the power of charging stations with static and dynamic signals (contributions C3.2 and C3.4).

- In the 2023 CIRED 27th International Conference on Electricity Distribution: contributing to objective O3, the user profiles were used to predict the share of each user profile in certain districts according to socio-demographic indicators with the objective of properly planning the required public charging infrastructure (contribution C2.3).

1.5 Thesis outline

This document has been structured into eight chapters:

- Chapter 1: Introduction. This chapter offers an overview of this thesis with a motivation section, the objectives derived from this motivation, an introduction to the research fields and the main contributions of this work.
- Chapter 2: Methodology. This chapter illustrates the clustering, modelling and simulation methodologies in block diagrams for a visual understanding, and the algorithms to simulate different EV control methods are also presented.
- Chapter 3: Article 1. Flexibility management of electric vehicles based on user profiles: The Arnhem case study. The first article of the compendium.
- Chapter 4: Article 2. Assessment of electric vehicle charging hub based on stochastic models of user profiles. The second article of the compendium.
- Chapter 5: Article 3. Enabling high penetration of electric vehicles using smart charging based on local and dynamic capacity limits. The third article of the compendium.
- Chapter 6: Main results and discussion. This chapter presents the main results and discussion of the work presented in each of the articles of this compendium.
- Chapter 7: Conclusions. This chapter presents the general conclusions of the thesis.
- Bibliography

Chapter 2

Methodology

This chapter introduces in a schematic way the methodology followed along with the different contributions of this paper. It splits in four research areas: clustering of EV user profiles, their modelling, usage of these models to simulate different scenarios and, finally, management of the flexibility that these EV users can provide. The following sections describe in detail the steps that constitute the guidelines followed in the development of the work.

2.1 Clustering of EV user profiles

The clustering methodology developed in this thesis consists of the following steps:

1. Sessions are divided into multiple sub-sets to improve the performance of GMM. The divisions are done by time cycle (e.g. day of the week) and disconnection day (i.e. day sessions, overnight sessions, 2-day sessions, etc.).

2. The clustering variables (i.e. connection start time and connection duration) are transformed into the natural logarithmic scale.

3. The outliers in the clustering variables are cleaned with a density-based clustering algorithm called DBSCAN.

4. The GMM clustering is performed with Expectation-Maximization (EM) algorithm. It is recommended to find the optimal number of clusters with the BIC approach.

5. The multiple clusters obtained are interpreted in terms of daily human behaviour and, therefore, combined with other similar clusters to form generic

user profiles. It is important to group them according to the centroid values but also the variance of the elliptical shape.

To illustrate the methodology, Figure 2.1 shows the scheme used for the Arnhem data set (see Chapter 3), where sessions from Monday to Thursday were considered a single "working day" time-cycle and differentiated from the Friday, Saturday and Sunday time-cycles.

This methodology was first introduced in the first journal article of this compendium, which is presented in Chapter 3. In a posterior conference article [19] the original methodology was improved by including outliers detection functions through DBSCAN clustering. This clustering methodology is contained in the open-source R package `evprof` [7].

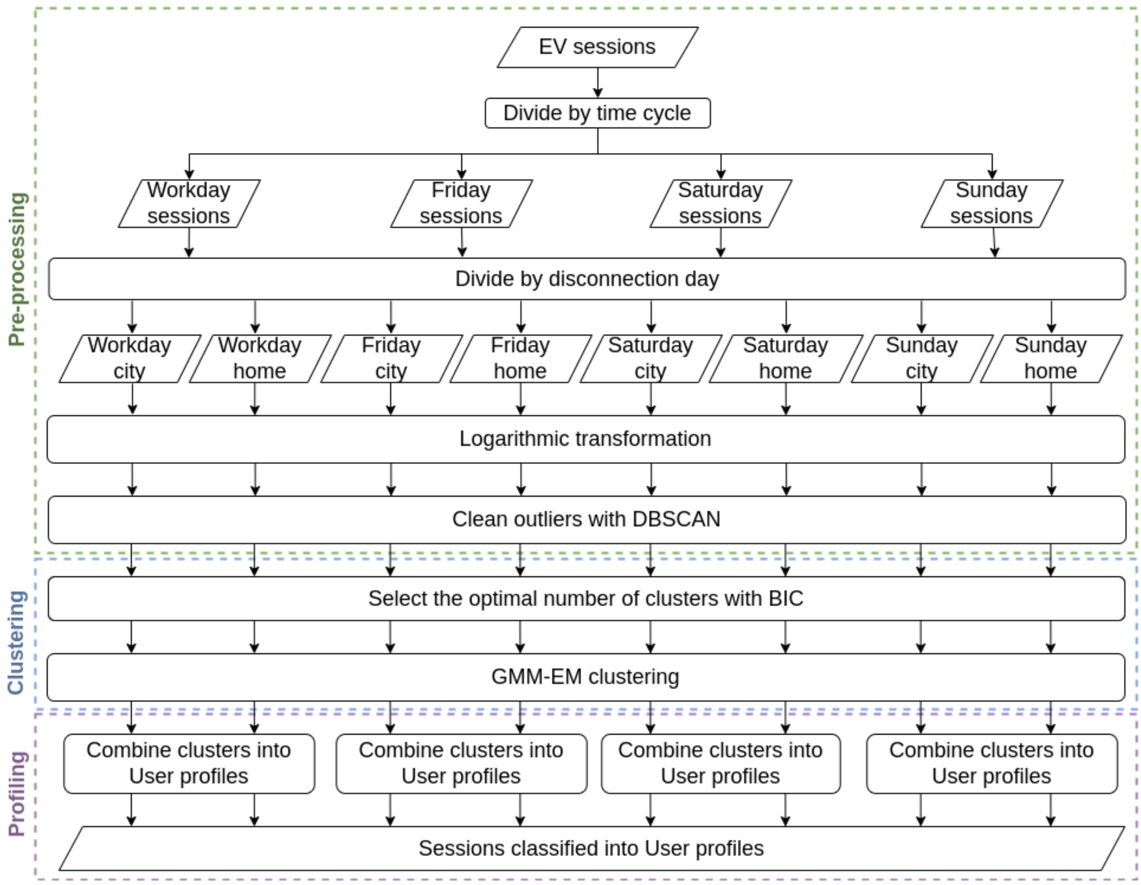

Figure 2.1: Clustering methodology scheme

2.2 Modelling EV user profiles

The modelling methodology developed in this thesis consists of the following steps:

1. The clustering methodology is performed in order to obtain the bi-variate GMM for the connection variables (i.e. connection start time and connection duration)

2. The sessions corresponding to every user profile are divided by charging rate. If the charging rate is not available this step is skipped.

3. For every charging rate sub-set perform the energy GMM clustering to obtain the parameters of the multiple Gaussian distributions describing the data.

4. The connection GMM, the energy GMM and more metadata information are used by a function from `evprof` package to build the EV model R object.

5. The EV model object can be saved as a plain text JSON file.

To illustrate the methodology, Figure 2.2 shows an example of a block diagram for one user profile and a single time cycle. The process is done for all user profiles and the final EV model is the combination of all user profiles' models for all time cycles.

More details about the methodology are found in Chapter 4, while a step-by-step tutorial with R support is provided on the `evprof` website [7]. The `evprof` package wraps all functions related to the clustering and modelling methodologies, and also provides a custom class object for the EV model, as illustrated in Figure 2.3, with a summary of the information contained in the model.

2.3 Simulating EV sessions

The methodology to simulate EV charging sessions based on the user profiles' GMM consists of the following steps:

1. Get the EV connections for every date in the date sequence:

2. Get the equivalent time cycle and the corresponding number of sessions per day, user profiles' ratios and user profiles' GMM

3. For every user profile simulate the EV connections according to the ratio of the user profile over the total number of sessions and its connection GMM

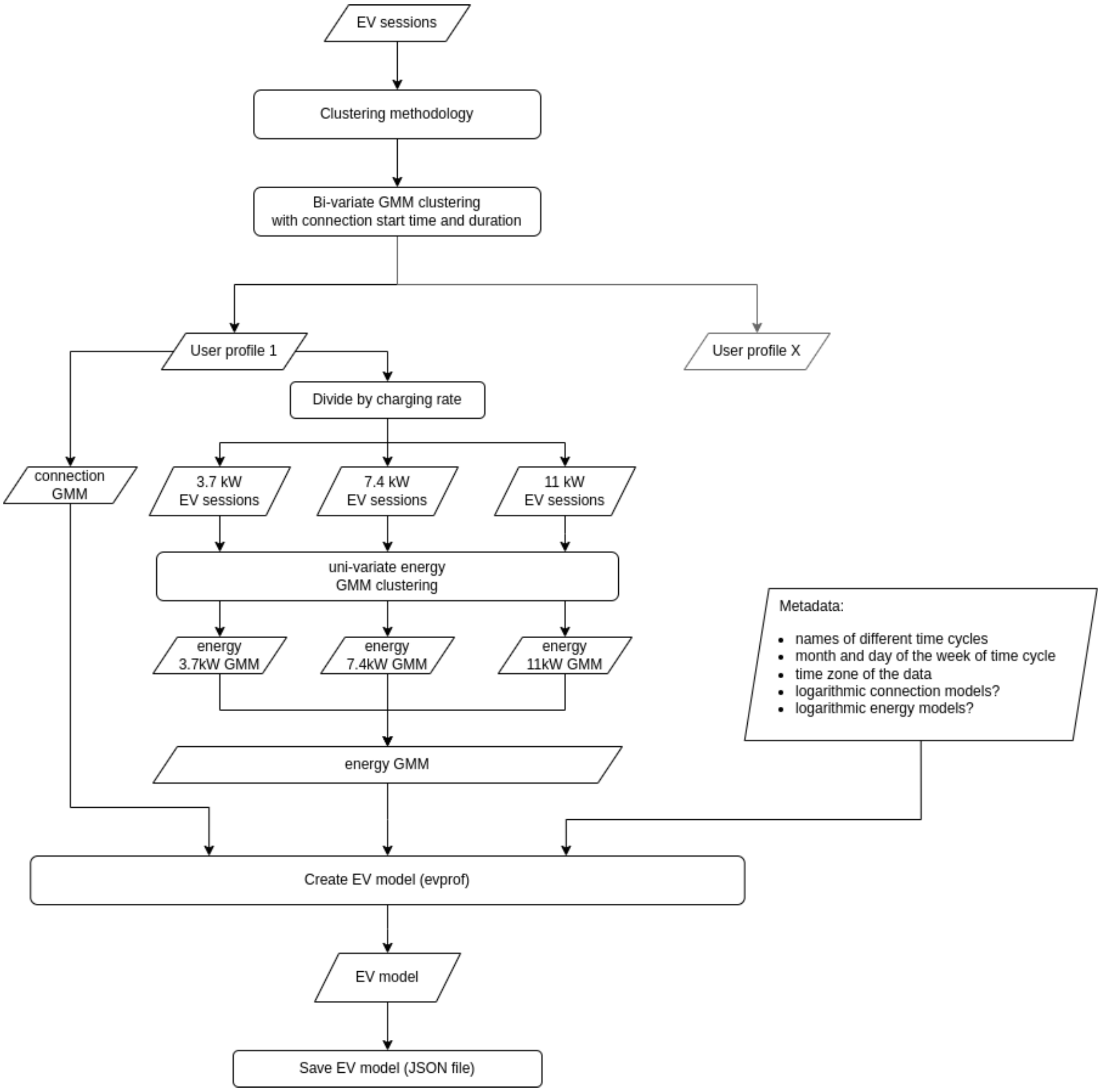

Figure 2.2: Modelling methodology scheme

4. Assign a charging power to every EV session according to the ratio of charging rates (e.g. 30% 3.7kW, 20% 7.4kW and 50% 11kW)

5. Simulate the energy for every session with the energy GMM corresponding to the time cycle, user profile and charging rate

6. Calculate the required charging time by dividing the energy by the power. If it is longer than the connection time then limit the charging time to the connection time.

```
> evmodel
EV sessions model of class "evmodel", created on 2022-09-21
Timezone of the model: Europe/Amsterdam
The Gaussian Mixture Models of EV user profiles are built in:
  - Connection Models: logarithmic scale
  - Energy Models: logarithmic scale

Model composed by 7 time-cycles:
  1. Monday:
     Months = 1-12, Week days = 1
     User profiles = Dinner, Shortstay, Visit, Worktime, Commuters, Home, Pillow
  2. Tuesday:
     Months = 1-12, Week days = 2
     User profiles = Dinner, Shortstay, Visit, Worktime, Commuters, Home, Pillow
  3. Wednesday:
     Months = 1-12, Week days = 3
     User profiles = Dinner, Shortstay, Visit, Worktime, Commuters, Home, Pillow
  4. Thursday:
     Months = 1-12, Week days = 4
     User profiles = Dinner, Shortstay, Visit, Worktime, Commuters, Home, Pillow
  5. Friday:
     Months = 1-12, Week days = 5
     User profiles = Dinner, Shortstay, Visit, Worktime, Commuters, Home, Pillow
  6. Saturday:
     Months = 1-12, Week days = 6
     User profiles = Dinner, Shortstay, Visit, Commuters, Home, Pillow
  7. Sunday:
     Months = 1-12, Week days = 7
     User profiles = Dinner, Shortstay, Visit, Commuters, Home, Pillow
>
```

Figure 2.3: Information from the “evmodel” class printed in the R console

7. Re-calculate the energy with the updated charging time (in case the charging time was limited by connection time)

Figure 2.4 illustrates the simulation methodology. This methodology was introduced in the journal article presented in Chapter 4 and later improved in the journal article presented in Chapter 5. The methods are also offered as an open-source R package, `evsim` [8], for better reproducibility.

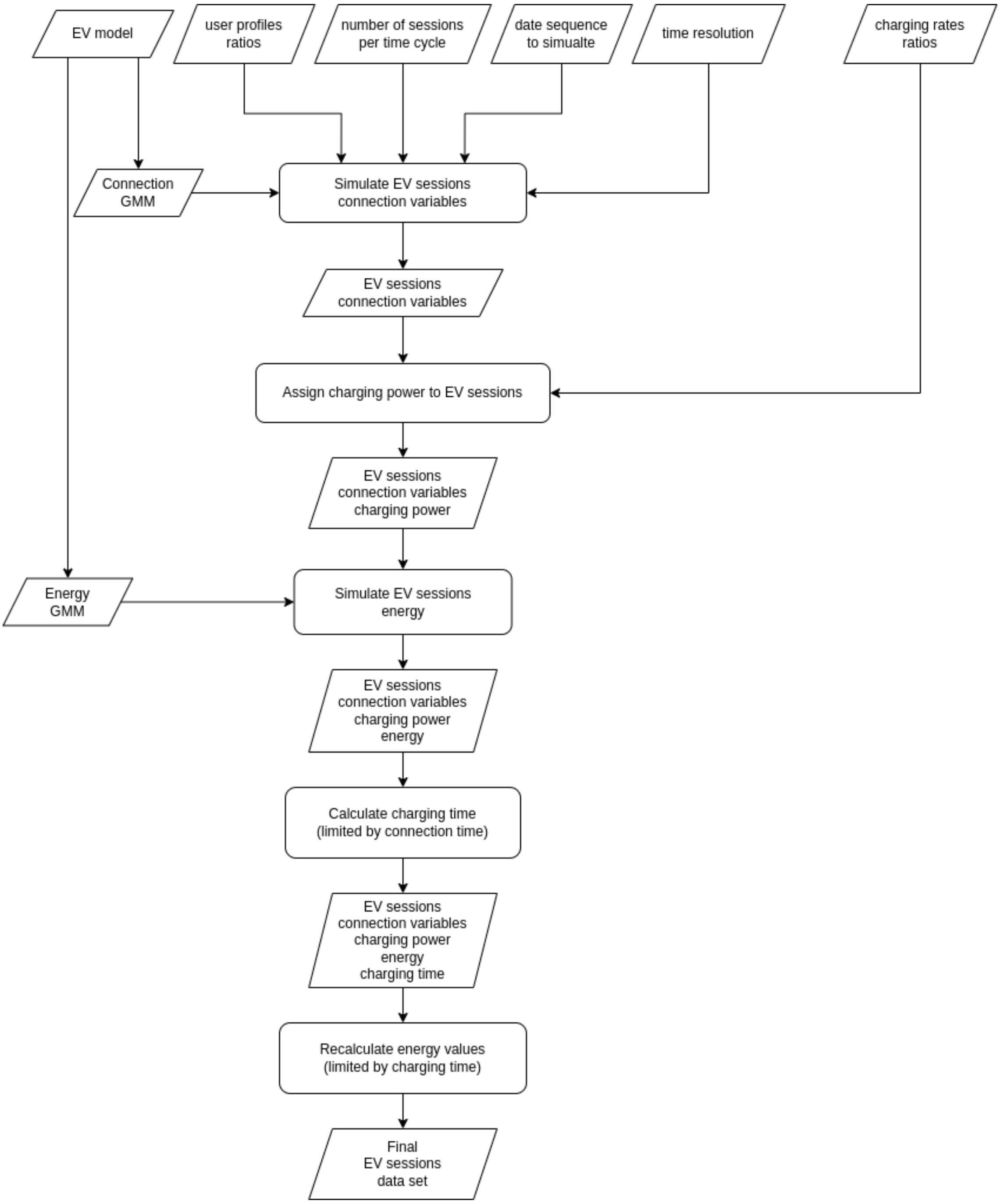

Figure 2.4: EV session simulation methodology

2.4 Flexibility management of EVs

In each one of the three journal articles of this compendium, a different EV flexibility management strategy is presented. Below are the algorithms that describe the following EV management methods:

- Postpone sessions (Algorithm 1): this method shifts the charging session over time according to power setpoint. The method is introduced in the first journal article, presented in Chapter 3, and the demand setpoint was calculated with a quadratic optimization.
- Limiting connection time (Algorithm 2): this method is not a smart charging strategy itself but a common regulation measure to manage EV demand in undersized charging areas. The method is introduced in the second journal article, presented in Chapter 4.
- Curtailing charging power (Algorithm 3): this method limits and adapts the charging power according to grid capacity signals and it is used in most smart charging applications due to its high flexibility. The method is introduced in the third journal article, presented in Chapter 5.

2.5 Validation data

During the development of this thesis, three different data sets of charging sessions, summarised in Table 2.1, have been used to validate the methodologies described in this chapter:

- Arnhem city: 259,419 charging sessions from 2015 to 2020, collected in the public charging infrastructure of the middle-sized Dutch city of Arnhem, which consisted of 270 different charging stations at the time, each with 2 charging points and a maximum charging power of 11 kW (three-phase 16A connection).
- Borg Harbour: 1807 sessions from 15 April 2019 to 4 May 2021, collected in the charging area of a Harbour in the Norwegian Harbour Borg Havn, which consisted of 8 different charging stations at the time, each one with 1 charging point and a maximum charging power of 3.7 kW (single-phase 16A connection).
- Amsterdam city: more than 2,683,938 sessions during 2020 and 2021, collected in the public charging infrastructure of the Dutch capital, Amsterdam, which consisted of 2713 different charging stations at the time, each one with 2 charging points and a maximum charging power of 11 kW (three-phase 16A connection).

Input : charging sessions schedule S, power setpoint time series O, time interval Δt, percentage of responsive users δ_{flex}
Output: modified schedule of charging sessions S

while *True* **do**
  Get L_t, total power demand timeseries from charging sessions
  Define T_{SHIFT}, a vector of time slot values where $L_t > O_t$
  if $length(T_{SHIFT}) = 0$ **then**
    break `/* No more flexibility required */`
  end
  $P_{SHIFT} = L_t(T_{SHIFT}) - O_t(T_{SHIFT})$ `/* power to shift in` T_{SHIFT} `time slots */`
  S_{FLEX} = sessions with potential to be shifted `/* i.e.` $TCHS_s = any(T_{SHIFT})$ `and` $F_s \geq \Delta t$ `*/`
  S'_{FLEX} = randomly select a percentage δ_{flex} from S_{FLEX}
  if $length(S'_{FLEX}) = 0$ **then**
    break `/* No more flexibility available */`
  end
  $TI = min(T_{SHIFT})$ `/* Time slot to shift sessions from */`
  S''_{FLEX} = sessions from S'_{FLEX} that start in TI
  Sort S''_{FLEX} from higher to lower F_s
  $PI = P_{SHIFT}(TI)$ `/* power to shift in` TI `time slot */`
  $s = 1$
  while $PI > 0$ *and* $s <= rows(S''_{FLEX})$ **do**
    <!– $s = S''_{FLEX}(s)$
    –> $TCHS_s = TCHS_s + \Delta t$ `/* Shift session a time slot */`
    $F_s = F_s - \Delta t$ `/* Reduce flexible time a time slot */`
    <!– $S(s_{id}) = s$ `/* Update original schedule with the modified session */`
    –> $PI = PI - P_s$ `/* Update the pending power to shift */`
    $s = s + 1$
  end
end

Algorithm 1: Postpone charging sessions according to power time series setpoint, for a single user profile

Input : Schedule of charging sessions S, number of charging points P, maximum connection hours H
Output: Modified schedule of charging sessions S

Limit the $ConnectionHours$ and $ChargingHours$ of all sessions up to H
$ConnectionEndDateTime = ConnectionStartDateTime + ConnectionHours$ `// Update connection end time`
$ChargingEndDateTime = ChargingStartDateTime + ChargingHours$ `// Update charging end time`
Get *dttmSeq*, the date-time sequence between the minimum connection start value and the maximum connection end value from sessions, with a time resolution of 15 minutes
Get *nConnections*, a vector with the number of vehicles connected at the same time, for every value of *dttmSeq*
Get *dttmSeqFull*, the values of *dttmSeq* when $nConnections > P$ `// Select the time slots with full occupancy`
`/* Don't charge sessions that start at a time slot with full occupancy */`
for *i in* 1 *to* $length(dttmSeqFull)$ **do**
  $ConnectionEndDateTime = ConnectionStartDateTime$ for sessions that start in $dttmSeqFull[i]$
  $ChargingEndDateTime = ChargingStartDateTime$ for sessions that start in $dttmSeqFull[i]$
end
`/* Include in` S `the new value of energy charged with time limitation */`
$EnergyCharged = (ChargingEndDateTime - ChargingStartDateTime) * Power$

Algorithm 2: Algorithm to limit the connection time of sessions.

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 3: Algorithm to simulate Flexpower

Use case	Number of charging sessions	Period	Number of charging points
Arnhem city	259,419	2015-2020	270
Borg Harbour	1,807	2019-2021	8
Amsterdam	2,683,938	2020-2021	2713

Table 2.1: Summary of data sets used for methodology validation

All these data sets contain the required variables for the clustering and modelling methodologies, i.e. connection start time, connection duration, energy charged and charging power rate, and other variables used in the flexibility management algorithms such as the session ID and charging point ID (in the case of Arnhem and Amsterdam).

Chapter 3

Flexibility management of electric vehicles based on user profiles: The Arnhem case study

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ABSTRACT

The ever-increasing global adoption of electric vehicles has created both challenges and opportunities for electrical grids and power systems as well as the market itself. Smart charging is broadly presented as a relevant opportunity to provide demand-side flexibility, benefiting both the user and the power system through flexibility aggregators. However, coordinating all sessions for the same optimization objective could be inefficient when the flexibility potential mismatches the flexibility demand. Instead, this paper proposes the user profile concept as a tool to group sessions into similar flexibility levels and then schedule the charging sessions of each user profile according to its most convenient optimization objective. Therefore, a clustering methodology based on a bivariate Gaussian Mixture Models is presented and validated with a real-world data set, resulting in seven different user profiles. The simulation of two smart charging scenarios, first coordinating all flexible sessions and second coordinating two selected user profiles, resulted in a more efficient scheduling in the latter case, obtaining similar results with a 35% fewer sessions shifted and the corresponding reduction in exploitation costs.

1. Introduction

The irreversible electrification of the mobility sector will open up an opportunity for a more efficient management of electricity grids thanks to the flexibility electric vehicles can provide. In this upcoming scenario, user participation and engagement are crucial (i.e. the concept of the energy citizen), and the management of EV charging sessions (smart charging) is seen as one of the key enabling technologies since it is technically easy to be incorporated into the energy value chain by intermediate agents such as aggregators or flexibility providers. Smart charging, as an optimization problem, can be addressed from different perspectives (e.g. demand response, energy community management, ancillary services) and objectives (e.g. peak shaving, local use of renewable generation, technical constraint from distribution grid, etc.) that result in different approaches to the problem, but all these use cases require an aggregator, an intermediate stakeholder that creates products capable of engaging the user and schedule flexible demand to satisfy the needs of the grid.

However, two main challenges arise when dealing with day-ahead (or intra-day) scheduling: accurate forecasting of participating charging sessions and reliable performance of smart charging algorithms capable of offering robust (reduced uncertainty) flexibility schedules with low computational costs. To date, the focus of research in this field has been on scheduling all charging sessions for a specific objective. In contrast, the methodology proposed in this paper decomposes the scheduling problem, optimizing each user profile according to its suitable flexibility objective, since the classification of EV sessions among generic user profiles (each with its own characteristic flexibility potential) can be used by aggregators as a tool to deliver smart charging in a more efficient and robust manner.

The first main contribution of this work aims to facilitate the task of aggregators with a clustering method to discover generic user profiles based on two simple attributes of the charging sessions: the start time and the duration of the connection. The objective is to aggregate users among similar daily connection patterns and, therefore, similar flexibility potential. Gaussian Mixture Models clustering is used to identify these rational clusters. The second contribution exploits this knowledge about user behaviour to create a selective smart charging strategy capable of satisfying multiple flexibility objectives through a targeted participation of sessions according to user profile membership. This reduces the uncertainty of the aggregated flexibility potential and the complexity of the optimization problem, reducing at the same time the number of sessions to exploit.

The work is structured as follows. Section 2 gives a short overview of the research into the fields of contribution undertaken in this paper. Section 3 details the methodology and methods used for the clustering

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process, while Section 4 describes the clusters obtained from a real data set and the subsequent characterization of these clusters into user profiles. Finally, Section 5 presents the smart charging algorithm and shows the value of introducing EV user profiles into a smart charging application. In this validation step, actual charging sessions data has been used in order to assess the results separately from quality of forecasting.

2. Related work

This section describes the current state of the art in the areas this paper contributes to the most: 1) clustering EV sessions among generic user profiles and 2) scheduling charging sessions to optimize the aggregated EV load.

2.1. User profile clustering

The main interest of this work is characterising user profiles with potential participation in flexibility programs. Thus, this work uses the terms 'user profile' or 'user behaviour' to refer to a daily connection pattern, defined by the beginning and end times of the EV session, or in other words, the connection start time and the connection duration. This approach gives a different perspective to the meaning of EV profile or EV user behaviour studied in other works that focus on the electrical demand of electric vehicles, which are based on charging profiles and power curves. There, the EV charging load is modelled using probabilistic density functions (PDFs), considering the initial and final State-of-Charge (SoC) per connection in [1], and the sessions start time, end time and distance driven in [2]. Users' demographics information such as the gender, the age and the education level is used in [3] to model different probabilistic models for charging load profiles simulation. The user behaviour is also referred in [4] to show the impact in the revenue of a charging infrastructure, defining the user behaviour with the arrival time, the dwell time and the energy demand. Other works have studied user behaviour in terms of charging frequency and the probability to charge at the end of the day. The probability of performing a domestic charge is modelled in [5] based on the final SoC of the daily distance driven. Similarly, the charging decision is modelled in [6,7] through the daily vehicle use, applying K-means clustering with the daily average speed as the feature vector, and using the clusters that the vehicle belongs to for simulating the charging load. The decision of the EV user about whether to participate or not in a demand-response program is also defined as user behaviour in [8,9], where users can choose among three different charging powers according to their time flexibility.

The focus of this work, however, is on the flexibility management of EV sessions; therefore we have explored the potential of *connection profiles* rather than analysing *charging profiles*. The methodology proposed in this work has the aim to discover generic connection profiles (i.e. user profiles) to increase knowledge on the potential flexibility of electric vehicles charging demand. Many studies aim to identify connection profiles according to the daily habits of car owners with different classifications or labelling: charging at workplace, at home or park-to-charge in [10,11]; office chargers, home chargers and visitors/taxis/car-sharing in [12]; full-time/part-time worker, unemployed people or professional driver in [13]; regular and random users in [14]; visitors and local users in [15]; stop&charge, park&charge, work&charge, home&charge and long sessions in [16]; or a deeper analysis in [17] with three types of office hours users, three types of overnight users and three types of non-typical users.

Despite data-driven methods are used in all these works to discriminate between these different EV user profiles, the complexity of the classification method and the variables used vary among them. Kim et al. [14] developed a hazard-based duration model of charging regularity (i.e. inter-charging times). A threshold value of the energy charged to differentiate between locals and visitors was used in [15]. K-means clustering combined with multilayer perceptron to improve classification was used in [18]. In [16], a multinomial logistic regression technique over a single variable (i.e. connection duration) was used, while a multivariate Gaussian mixture model with four variables (i.e. session start time, connection duration, hours between sessions and distance between sessions) was performed in [17]. In [10–12], a two-variable density-based clustering method is addressed with DBSCAN clustering. Session start time and session end time are used for that purpose in [10] [11], and sessions start time and connection duration in [12].

In this paper, the user profiles are not defined *a priori,* Mixture Models (MM) are used to discover them. MM have been chosen as the clustering method for three main reasons. First, [19] exposes that density-based clustering like DBSCAN results in a complex clustering process when different regions of the data space have considerably different densities. In terms of EV charging sessions, this is highly probable since each study case will have some principal user profiles. Second, research carried out into profiling electrical consumption patterns in residential loads shows that MM are better in smoothing out random effects because clustering itself considers the correlation and trends of the variables [20]. In terms of the charging sessions, human behaviour contains an important random component resulting from the different elements that can interfere with our timetables (e.g. traffic lights, traffic, longer-than-scheduled meetings, etc.). And third, another advantage of using MM over K-Means or DBSCAN methods is that the output directly gives both the clusters and the associated models, so modelling each cluster afterwards as done in [11,18] or [1] is not necessary. On the other hand, the decision as to how many variables to include in your data-driven method depends on the availability of the data. The data sets used in [16,17], for example, have an ID variable showing the unique RFID codes of the vehicles. This variable allows a tracking study of the vehicle to be carried out and adds value to the models in terms of travel distance and charging frequency. However, the available data sets may not contain this information, so this work has considered only common variables for any charging infrastructure to undertake a study which is as general as possible. Therefore, the contribution of this paper to the field of user profiles is a methodology reproducible for any charging sessions' data set, using a robust clustering method scarcely exploited in this field (i.e. Gaussian Mixture Models with Expectation–Maximization) based on two basic variables (i.e. connection start time and connection duration).

2.2. Smart charging algorithm

The classification of sessions into generic user profiles paves the way for the second contribution of this work, a smart charging algorithm based on these profiles. The past decade has seen prolific research into smart charging methods for multiple objectives (e.g. increasing self-consumption of local solar energy, balancing load, reducing energy cost, increasing users profit, etc.), with different configurations (e.g. centralized control, distributed charging, public charging stations, residential buildings, etc.) and diverse optimization methods (linear programming, quadratic programming, meta-heuristics, etc.) [21].

This work presents a smart charging algorithm from the aggregator perspective, with a centralized control in the aggregator figure to schedule and coordinate charging sessions according to a defined objective. A centralized scheduling control is more likely to reach an optimal charging strategy on the system level, since it considers the aggregation of renewable generation and electrical demand in the whole system [21]. Important research has emerged in this field, showing a wide variety of optimization methods and objectives. A two-step Linear Programming (LP) optimization is presented in [22] to reduce the energy demand peak and charging cost shifting sessions from high cost periods to lower cost periods. A LP optimization is also applied in [23] to reduce the power peak demand in a parking lot using valley-filling strategy, and in [24] to reduce the light flicker due to PV fluctuations. A Quadratic Programming (QP) optimization is carried out in [10] for two different scenarios, load balancing and load flattening, to increase the consumption of renewable energy through EV charge. The PV energy self-consumption is also increased with EV optimization in [25], using Particle Swarm Optimization (PSO). The generation costs of supplying the EV load are minimized in [26] with a Mixed-Integer Linear Programming (MILP) optimization. The maximization of the EV aggregator revenue, or minimization of the energy cost, is one of the most used objectives, as seen in [27] [28] using MILP optimization, in [8] with LP, in [29] with non-linear programming or in [30] [31] with QP.

However, most of these works consider all the sessions in the scheduling problem individually, therefore requiring complex mathematical models to solve the optimization problem and define a specific charging power for every EV and time slot. For a large number of sessions in a day-ahead smart charging scenario, obtaining all sessions' schedule from the same optimization problem implies a high computational cost and time. To cope with this complexity of the EV scheduling problem, the Alternating Direction Method of Multipliers (ADMM) is presented in some works as an emerging technique for large-scale optimizations, since it decomposes the original objective function into multiple problems to solve in parallel [31] [24].

On the other hand, the cornerstone of aggregators when participating in demand response programs is the *a priori* quantification of the flexibility capacity. That is, the aggregated power that can be allocated at a specific time to satisfy a certain flexibility demand, directly related with the size and behaviour of the aggregated EV users. The knowledge of generic user profiles among sessions and their characteristic flexibility potential could help the aggregator to define a more feasible objective in the optimization problem suited to each user profile separately. Therefore, in contrast to the complex scheduling optimization models raised in other works, this paper decomposes the smart charging method in the following steps to reduce the flexibility uncertainty and the complexity of the optimization problem: (i) the suitable user profiles to accomplish the aggregator's optimization objectives (e.g. peak shaving, solar use, etc.) are selected according to their flexibility potential; (ii) a quadratic optimization is performed to find the optimal aggregated power demand curve (i.e. setpoint) for each user profile according to their optimization objective; (iii) a postpone algorithm is applied to the charging sessions that have agreed to participate in the demand-response program, until the aggregated power demand matches the setpoint.

The division of the method between a time-series optimization and a scheduling algorithm results in a fast computation, at the same time that separates the objective of the demand-response program and the smart charging deploying strategy (e.g. postpone, power modulation, etc). All references above mentioned optimize the charging power of the vehicles for every time slot. This is an optimistic approach since achieving the optimal charge depends on the charging infrastructure (if the charging point has a power modulation feature) and the vehicle (if the vehicle accepts charging with the desired power). Therefore, this work proposes the *Postpone* method as smart charging strategy since it is more widely applicable.

Finally, the algorithm proposed considers the option for EV users to not participate in the demand-response program. In a real implementation of a demand-response program, not all users are willing to participate even though they could provide flexibility, and this response factor must be contemplated by the aggregator [9]. Therefore, we have introduced a *responsive ratio* parameter in our algorithm to randomly select a percentage of sessions that take part in the smart charging program and simulate a more realistic demand-response scenario.

3. Charging sessions clustering methodology

This section describes the proposed methodology for clustering sessions among representative user profiles. In this work we understand the user profile as a generic daily connection pattern rather than the charging (i.e. demand) profile since we do not focus on the EV demand but rather on the EV flexibility. For example, people who arrive at their workplace every working day around 9:00 and go back home around

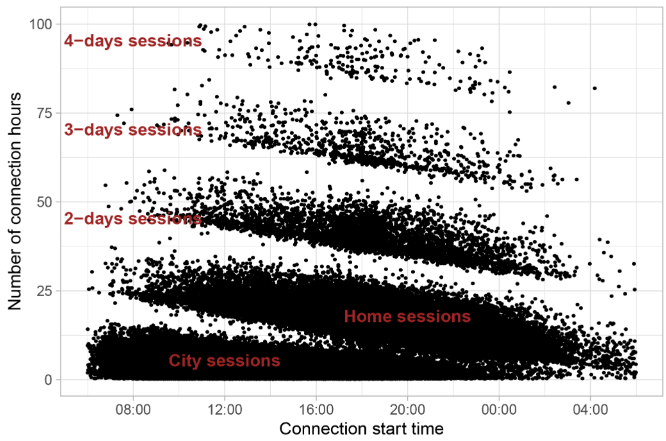

Fig. 1. Charging sessions from the data set of this work.

18:00. Thus, the clustering process has been carried out considering the connection start time and the connection duration as clustering variables. We have assumed that the energy required in one session is not an inherited variable of users' connection pattern and it can vary from day to day and from user to user and consequently this has not been used as a discriminant variable for clustering. Since the methodology proposed considers only these two connection variables, it can be reproduced to any other charging sessions data set, even with anonymous charging sessions without a vehicle or user identifier like the data set used in this case study. The method proposed for discovering and modelling EV user profiles, follows four steps:

1. Division of the data set into sub-sets.
2. Logarithmic transformation of variables.
3. Clustering with Gaussian Mixture Models (GMM) and Expectation–Maximization (EM) algorithm.
4. Characterization of clusters into user profiles.

3.1. Data division

To perform an accurate distribution-based clustering and obtain precise and generic stochastic models for user profiles, the original data set has been divided into several sub-sets according to time cycle and disconnection day.

3.1.1. Time period

The daily habits of citizens change according to the day of the week, the season, holidays, etc., therefore so too does the charging behaviour of the EV users. This is particularly evident for working days (weekdays hereinafter) and weekends, but there are some other cases that could be of interest depending on the community under study. For example, inbound and/or outbound tourism activity during a day or the impact of school holidays. As a result, the distribution of sessions over the day (and the corresponding user profiles) may not always remain the same. Previous studies [10] [11] [1] have analysed the user profiles for weekdays and weekends separately. The method raised in this study does not predefine any time period or duration for the profiles, thus allowing it to discover and model arbitrary user profiles. That said, however, for this study case we have also divided the data set between weekdays and weekends.

3.1.2. Disconnection day

A scatter plot of charging sessions represented according to the connection start time and the connection duration in hours is shown in Fig. 1. Note the visible aggregations of sessions separated by blank ribbons; this is a first sign of different user profiles. Since the addition of the connection duration to the connection start time corresponds to the disconnection time, these blank ribbons represent that vehicles disconnecting at dawn, concretely from 2 to 6 a.m, is not usual. Thus, the different "clouds" in the figure represent the EV sessions that disconnect on the same day of the connection, the day after, two, three, or four days after. As said, this work focuses on daily behaviours, daily connection patterns, so the most relevant groups of sessions are those that disconnect on the same day - labelled *city sessions* - and those that disconnect the following day - labelled *home sessions*.

These different groups of sessions have different density and, since Mixture Models are based on the density distribution of the samples, it is convenient to divide the data into smaller sets in order to obtain better defined distributions shapes to be translated into Gaussian Mixture Models (i.e. clusters).

3.2. Logarithmic transformation

A common practice before applying Mixture Models clustering techniques is to transform the objective variables with the aim of obtaining better distribution shapes to model. Similarly to [17], we apply a logarithmic transformation to our objective variables (i.e. connection start hour and number of connection hours) to reduce sparsity between sessions and increase the density of sessions, so a model-based clustering method such as GMM performs better. Moreover, these variables are defined as only positive, so they present asymmetric distributions. Since Gaussian distribution is by nature symmetric and unbounded, the logarithmic transformation improves normality of time data resulting in better and significant results when applying GMM.

3.3. Clustering

The clustering method used for clustering charging sessions is a bivariate Gaussian Mixture Models (GMM) with Expectation–Maximization (EM) algorithm. On one hand, the strong relationship that Fig. 1 shows between the start time and the duration of EV connections (the later the vehicle connects, the lower the connection duration is), is a sign of a *not null covariance* between these two variables and justifies the use of bivariate Mixture Models, which model the covariance between the two components. Moreover, the Expectation–Maximization (EM) algorithm allows cluster membership to be considered a probability instead of a hard assignment, which makes possible the pertinence to several clusters. This probabilistic classification is convenient due to the random nature of charging sessions and the daily human behaviour. On the other hand, the Gaussian distribution has been selected as the parametric model since the charging sessions are independent and the number of occurrences added at every instant of time is large enough to guarantee a normal distribution, independent of their individual distribution (i.e. the Central Limit Theorem). Thus, considering a user profile as the population and the corresponding data set charging sessions as the sample, and assuming that the sample size is large enough, the density distribution of each cluster can be defined by a bivariate Gaussian distribution.

The use of GMM-EM clustering method requires defining a specific number of clusters. A widely-used strategy to choose the proper number of clusters is to apply the clustering with all desired options of number of clusters and compare their performance using the Bayesan Information Criterion (BIC). The BIC indicator is the value of the maximized log-likelihood with a penalty on the number of parameters in the model. This allows a comparison of models with different parameters or different numbers of clusters. In general the larger the value of the BIC, the stronger the evidence for the model and number of clusters [32]. Once the number of components to explore is defined, then the EM algorithm initializes their parameters, concretely the mixture weight (π), the means vector (μ) and a covariance matrix (Σ) in the case of GMM. After initialization, EM iterates between Expectation–Maximization steps until the log-likelihood function of our model converges with the predefined tolerance. In the following, the main equations of the Expectation–Maximization process are detailed, and the corresponding nomenclature described in Table 1.

Table 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)

The log-likelihood is computed with Eq. (1), refering 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. (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. The initialization is important in EM iteration, so the log-likelihood is used to select the optimal result of several iterations.

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

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

3.3.1. Expectation step

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. (3).

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

Therefore if x_i is very close to one Gaussian distribution c, it will obtain a high r_ic value for this Gaussian and relatively low values otherwise.

3.3.2. Maximization step

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

$$m_c = \sum_i r_{ic} \tag{4}$$

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

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

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

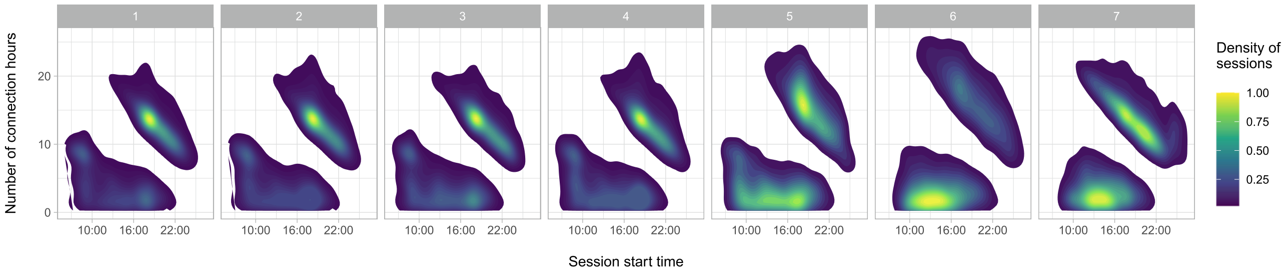

Fig. 2. 2D density plots of sessions by weekday (starting on Monday).

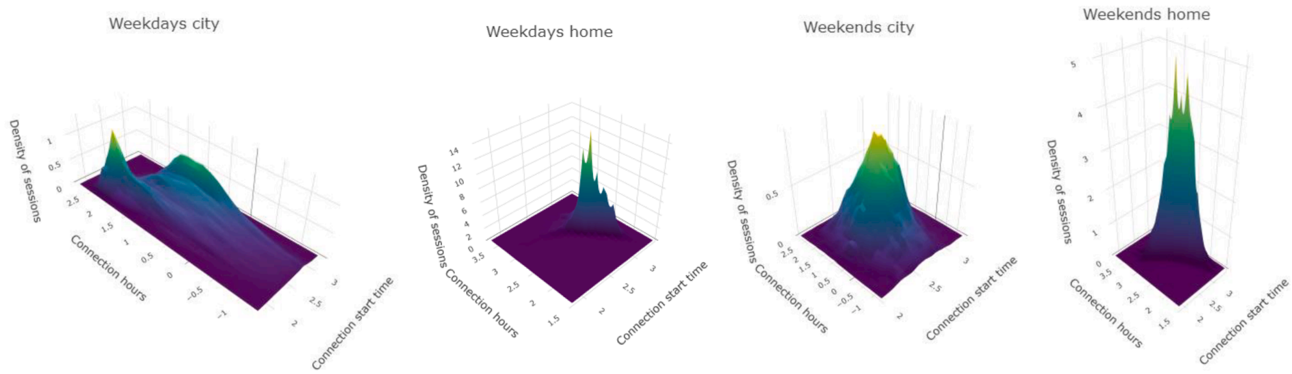

Fig. 3. 3D density distribution plots.

4. Case study: The Arnhem public charging infrastructure

In this section, the methodology presented in Section 3 has been validated with a large data set of EV charging sessions from the middle-sized city of Arnhem, The Netherlands. The data set is composed of 259,419 charging sessions from 2015–08-31 to 2020–06-01 (more than 300 sessions per day in 2020) collected in the Arnhem's public charging infrastructure, which contains 270 different charging poles, each with 2 charging slots with a maximum charging power of 11 or 22 kW (depending on the pole). In fact, analysing just public charging infrastructure data is not a limitation since the 75% of the households in the Netherlands are dependent on public charging facilities and DC charging is not widely used [17].

From the original data set, we discarded 10.3% of sessions considered errors, resulting in a clean data set of 232,583. The sessions with the following characteristics were discarded: energy equal to 0, connection duration less than 15 min, charging duration higher than connection duration, or charging power higher than the maximum power that the public charging infrastructure of the study case can supply (i.e. 22 kW for Arnhem).

Besides, as pointed out in Section 3.1.2, sessions that finished two or more days after the connection, as seen in Fig. 1, have not been considered since they represent only 3% of the clean data set and therefore they are not a generic user profile object of this study. Probably in future research, these long-connection sessions could provide interest on V2G technology due to the potential of being charged and discharged as a battery connected to the public grid. It the end, the final Arnhem's data set consists of 225,040 sessions.

4.1. Preparation of data before clustering

Following the methodology outlined in Section 3, the first step is to explore different density distributions on the data according to time cycles. Even though a large difference in session distributions between years or months is not observed, a relevant difference between weekdays does stand out. In Fig. 2, we can see a similar distribution pattern from Monday to Friday, and different density shapes for Saturdays and Sundays. During weekdays most EVs charge during the evening - probably after working hours - with long connection durations. In contrast, during weekends most sessions have short connections and throughout the day, probably due to brief visits to the city. We have considered two main different time cycles according to the distribution homogeneity in the sessions' distribution, i.e. two different models: *weekdays* and *weekends*.

Besides this, as pointed out in Section 3.1.2, for each time cycle we can distinguish two different groups of sessions, labelled as city and home sessions, according to the disconnection day. In total, four different subsets of sessions will be submitted independently to the GMM clustering process: weekdays city, weekdays home, weekends city and weekends home. Another step before clustering is the logarithmic transformation, explained and justified in Section 3.2. Fig. 3 shows the distribution shapes of the four subsets in the logarithmic scale. This figure justifies the need to divide the data before applying GMM clustering. Each subset contains a clearly different distribution and, moreover, the existence of different peaks of density is an indicator of a mixture of different models (i.e. clusters). Additionally, the big difference between density values in some of these subsets justifies the choice of distribution-based clustering over density-based clustering (e.g. DBSCAN), considering the complexity to find different clusters with a single configuration of parameters when the density differences are so relevant [19].

4.2. Clustering and characterization of user profiles

Arnhem's charging sessions data set has been divided into four subsets (weekdays/weekends city/home sessions), with a transformation of the clustering variables to a logarithmic scale. In this section, a GMM-EM clustering process has been applied to each one of the sub-sets in concordance with the methodology presented in Section 3. The mclust R package [33] has been used for the clustering process. First, the BIC approach has been applied to each sub-set, considering from 1 to 15 clusters (see Figures A.1 - A.4 in Appendix A.1). Considering the number of components from which the BIC indicator stops decreasing, the

Weekdays (74 %)	City sessions (48 %)	Cluster 1 (10 %)	**Worktime (10 %)**
		Cluster 2 (17 %)	**Visit (36 %)**
		Cluster 6 (19 %)	
		Cluster 3 (24 %)	**Shortstay (40 %)**
		Cluster 4 (3 %)	
		Cluster 5 (13 %)	
		Cluster 7 (14 %)	**Dinner (14%)**
	Home sessions (52 %)	Cluster 2 (6 %)	**Commuter (23 %)**
		Cluster 6 (17 %)	
		Cluster 1 (16 %)	**Home (35 %)**
		Cluster 7 (5 %)	
		Cluster 8 (14 %)	
		Cluster 3 (15 %)	**Pillow (41 %)**
		Cluster 4 (9 %)	
		Cluster 5 (17 %)	
Weekends (26 %)	City sessions (53 %)	Cluster 1 (29 %)	**Shortstay (46 %)**
		Cluster 5 (6 %)	
		Cluster 6 (10 %)	
		Cluster 7 (1 %)	
		Cluster 4 (16 %)	**Dinner (16 %)**
		Cluster 2 (8 %)	**Visit (38 %)**
		Cluster 3 (30 %)	
	Home sessions (47 %)	Cluster 1 (14 %)	**Home (59 %)**
		Cluster 4 (18 %)	
		Cluster 6 (7 %)	
		Cluster 7 (19 %)	
		Cluster 2 (11 %)	**Pillow (41 %)**
		Cluster 3 (21 %)	
		Cluster 5 (9 %)	

Fig. 4. Classification of sessions into user profiles with proportions.

Table 2
Average features or user profiles.

Profile	Average start time	Average connection duration (h)	Average charging duration (h)	Average charging power (kW)	Average energy (kWh)
Worktime	09:34	8.66	3.07	3.99	12.93
Visit	13:24	4.26	2.62	4.51	12.23
Shortstay	14:35	1.28	1.16	4.73	5.54
Dinner	19:00	3.74	2.67	4.64	12.81
Commuter	19:14	13.65	3.52	3.73	13.77
Home	18:12	17.89	3.64	3.96	15.32
Pillow	22:13	11.78	3.63	4.18	15.97

following number of components have been selected for each subset: 7 clusters for Weekdays city sessions; 8 clusters for Weekdays home sessions; 7 clusters for Weekends city sessions; and 7 clusters for Weekends home sessions.

In all cases, the convergence in the fitting process came from VVV models (i.e. ellipsoidal distribution, varying volume, varying shape and varying orientation). The corresponding ellipses of every component and every subset are shown in Figures A.5 - A.8. Each ellipse defines a bivariate Gaussian distribution and its centre represents the average start time and average duration of sessions belonging to that group. Behind the numbers we can interpret a user behaviour in terms of timetable. For a better readability, an exponential transformation has been applied to the centroids of each cluster to translate the logarithmic values into time in hours.

At this point, it is appropriate to add a second-step classification, or profiling step. Each cluster has been labelled with a generic user profile according to their respective interpretations. Thus, each user profile can be assigned multiple Gaussian Mixture Models with the corresponding weights or probabilities. The authors' interpretations of each cluster and the user profiles assigned to them are shown in Tables A.1 - A.4 of Appendix A.2. Our interpretations have not only been based on the values of connection start time and duration of the centroid of each cluster, but as well on the shape of the corresponding ellipses (see Figures A.5 - A.8), which represent the covariance matrix of each cluster. A wider ellipse means a less concrete definition of the user profile. In this way, we have defined very specific user profiles like Worktime (starting around 09:00 for 8-9 h), Dinner (starting around 19:00 for 3-4 h), Commuter (starting after work at 18:00–19:00 for 12–14 h) and Shortstay (duration for less than 1 h), and more general user profiles like Visit (dispersed around the day and varying duration), Home (starting during daytime and connected until the next day) and Pillow (starting during evening-night and connected until the next day). Worktime and Commuter profiles are present only on working days since these are behaviours resulting from work timetables.

Fig. 4 summarizes the clustering process and the user profiling step, showing the different categories found and the corresponding weights of each model. The number of the cluster corresponds to the numbers of Figures A.5 - A.8 of Appendix A.2.

Table 2 shows the average values for the features that define every user profile. Observe that all user profiles, apart from the Shortstay, remain connected longer than charging, and therefore have flexibility hours (i.e. difference between connection and charging times). In fact, for this data set 49.9 % of sessions have more than 5 h of flexibility, and a 56.3% more than 2 h. In the case of the Worktime, Commuter, Home and Pillow profiles, the number of flexibility hours is highly considerable. It can be observed that the charging time is similar for all profiles, with the exception of Shortstay users whose charging time is limited by the connection time. This is a consequence of a similar energy being required for most sessions, concretely between 9 and 16 kWh, independent of their user profile.

Another way to validate the clustering process and the corresponding characterization of each cluster, is to visualize the demand power profile for all EV user profiles. Fig. 5, for instance, shows the demand curves of each user profile for a week in January 2020 The demand curves have been calculated with time intervals of 15 min, using the connection start time, the energy charged and the charging power of each real session. The demand of each profile can be seen to correspond to a specific time-

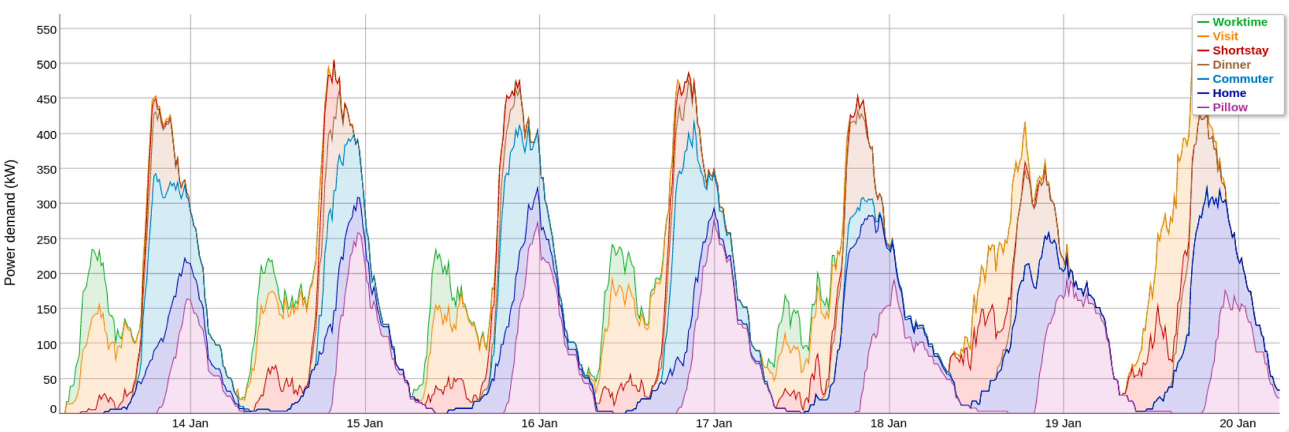

Fig. 5. Arnhem's EV real demand by user profile.

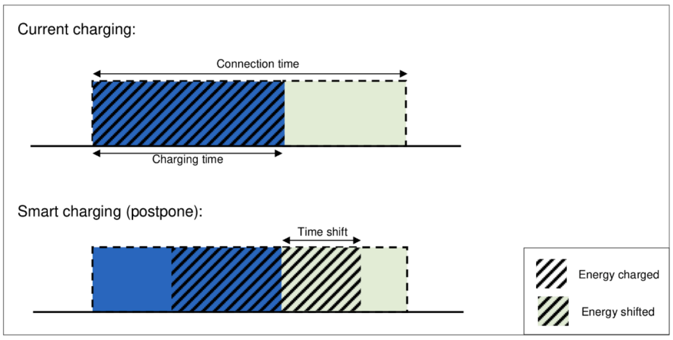

Fig. 6. Smart charging with Postpone method.

Table 3
Nomenclature.

Parameter	Description
T	Number of time intervals within the optimization window
Δt	Time interval, in hours
$TCONS_s$	Connection start time of a session
$TCONE_s$	Connection end time of a session
$TCHS_s$	Charging start time of a session
$TCHE_s$	Charging end time of a session
P_s	Charging power of a session
F_s	Flexible hours (i.e. connection hours – charging hours) of a session
S_{FLEX}	Sessions with flexibility potential
P_{FLEX}	Flexibility potential, in power units
w_1	Weight for grid balance optimization strategy
w_2	Weight for peak shaving optimization strategy
S_t	Solar generation time series
L_t	Static EV load (BAU) time series
V_t	Flexible EV load (BAU) time series
O_t	Optimal flexible EV load time series
E	Total energy demand from flexible EV within the optimization window
δ_{flex}	Percentage of users responsive to the flexibility program
T_{SHIFT}	Timeslots where power demand is higher than the setpoint
P_{SHIFT}	Power to shift from one time slot to the following, considering the setpoint

range according to the sessions' start time. At the same time, morning and evening peaks and a big valley during midday stand out from the total demand curve on weekdays (i.e. 13th – 17th January), while during weekends (i.e. 18th and 19th January) there is a wider and irregular demand profile. This validates employing different models for weekdays and weekends.

5. Flexibility management based on user profiles

In this work, we pursue a smart charging strategy capable of adapting charging sessions to cope with a flexibility demand as a result of participating in a specific program through an aggregator. The purpose of activating such flexibility can accomplish many different goals, from solving technical constraints at DSO level, to peak shaving or simply efficient use of local RES. EV owners are interested in participating in such programs because it implies a monetary benefit, or similar incentive, without affecting their daily habits and thus resulting in a win–win scenario.

However a common drawback is that flexibility potential usually mismatches flexibility demand, so it is extremely important for the aggregator to have information about the typology of EV users and their connection patterns, in order to offer a feasible flexibility demand to the suitable EV users. From here on, instead of rescheduling all sessions according to the same optimization objective, this paper extends the existing EV coordination methodologies by associating each user profile to a particular optimization objective.

Another important point of smart charging is the way that the session is modulated. Traditionally, the charging profile of an EV can be modelled as a power step lasting a certain time and starting as soon as the vehicle is connected. In that sense, a charging session could provide flexibility in terms of time (i.e. the charge is postponed or divided into several shorter sessions), power (i.e. the charging rate is modified) or energy (i.e. the user agrees to finish the session without reaching 100%, or transferring energy to the grid, in the case of V2G). This work only considers flexibility potential in terms of time, i.e. the smart charging postpone method depicted in Fig. 6 showing the exploitation of the difference between connection and charging times to postpone the session.

In this section, first the flexibility potential of every user profile is quantified to offer an overview of the difference between the available flexibility levels (in terms of power and time) among user profiles. Next, a smart charging algorithm is proposed to emulate the individual response and estimate the impact of this flexibility when activated in different scenarios. The nomenclature used in this section is described in Table 3.

5.1. Quantification of flexibility potential

Quantifying the flexibility potential of a power demand curve offers a valuable tool for measuring the impact of shifting a specific amount of power from one time slot to another. Inspired by the definition of demand response potential from Develder et al. [11], we define the potential flexibility of a session lasting a time interval $[t, t + \Delta t]$, within the connection interval $[TCHS_s, TCONE_s]$, as its charging power P_s, if the following statements are true:

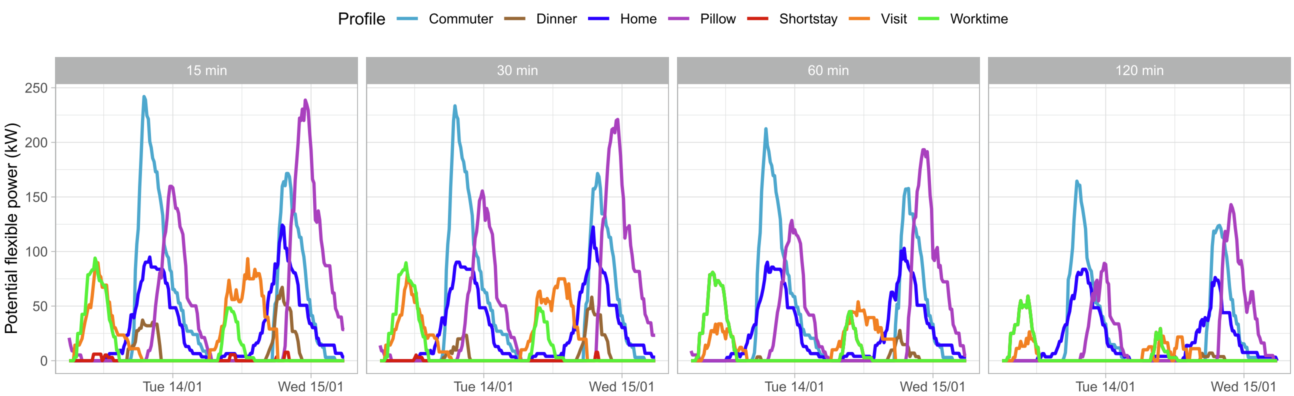

Fig. 7. Flexible power potential by user profile.

1. The vehicle starts charging during this time slot

$$t = TCHS_s \tag{8}$$

2. The vehicle remains charging during the entire time interval

$$[t, t + \Delta t] \subset [TCHS_s, TCHE_s] \tag{9}$$

3. The charging session can be shifted an interval Δ within the connection interval

$$TCONE_s - TCHE_s \geqslant \Delta t \tag{10}$$

When considering all sessions under these statements as $S_{FLEX(t,t+\Delta t)}$, then the aggregated flexible power within the time interval $[t, t+\Delta t]$ is:

$$P_{FLEX(t,t+\Delta t)} = \sum_{s \in S_{FLEX(t,t+\Delta t)}} P_s \tag{11}$$

Eq. (8) has been added to the Develder et al. [11] definition because the only smart charging strategy we consider here is the Postpone method. To postpone the charging start time of a session from time t to time $t + \Delta t$, the session must start charging at time t (i.e. $t = TCHS_s$). Without this constraint, the smart charging method would consider dividing a session into shorter sessions as well, shifting only part of the session instead of the full session.

We have approximated all start times on a 15-min basis since this is a realistic time-base for charging sessions and offers sufficient granularity to participate in different markets and services (e.g. balancing, congestion management). No distribution grid capacity or power system constrains have been considered in this case. Fig. 7 shows the flexibility potential (power vs time) for every existing user profile during two representative days in January 2020, Monday 13th and Tuesday 14th, and considering different time granularity (Δt) of 15, 30, 60 and 120 min. The curves have been obtained by applying the definition of Eq. (11) to the profiles obtained in the analysis from Section 3.

First, it can be observed that the longer the time granularity, the lower the flexibility potential. This is because the probability of having sessions that accomplish the three conditions: Eqs. (8)–(10) decreases with longer time intervals. Note that considering the Postpone strategy is a constraint and for other Smart charging strategies the equations should be modified accordingly. For this study case, there would not be a significant difference if it were to participate in a flexibility market, or demand-response services, with scheduling intervals of 15 or 30 min; but a flexibility management with 120-min time intervals would not be feasible.

Fig. 7 also shows a considerable difference for the potential flexibility between user profiles. As seen in Table 2, most of the user profiles have similar charging duration, while the connection duration varies considerably. This results in higher flexibility potential for user profiles with longer connections. In that sense, Commuter profile has the highest flexibility peak in the evening, followed by Home profile, while Pillow profile has the flexibility peak at night. At the same time, Worktime profile has its flexibility peak at early-morning, while the flexibility potential of Visit profile is more irregular throughout the morning. Finally, Shortstay and Dinner profiles have too short connections in order to deliver a relevant flexibility potential. Note that despite the big difference between the number of sessions of Visit and Worktime profiles (36% for Visit profile and 10% for Worktime profile for Weekdays, see Fig. 4), the level of flexibility is similar. The same happens with Commuter and Home profiles and, therefore, this shows the importance of grouping sessions among user profiles when the objective is to manage their flexibility.

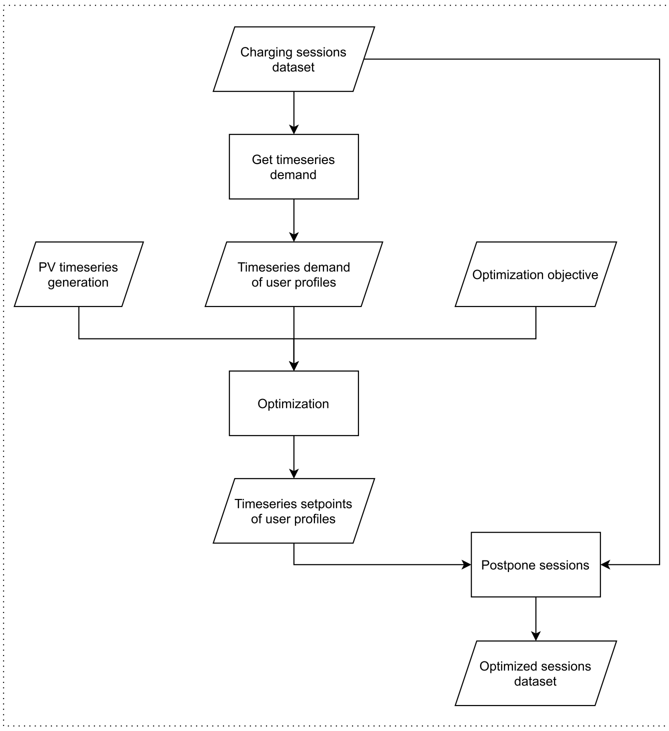

Fig. 8. Smart Charging diagram.

5.2. *Smart charging algorithm*

The novelty of the smart charging strategy proposed in this section consists in using the previously-identified EV user profiles to address the flexibility management process, specifying a particular objective to a particular user profile. This strategy allows *a priori* estimation of flexibility based on the user profiles and reducing the uncertainty during both the scheduling and activation stages. Thus, the output of the smart charging algorithm modulates the charging start time (postpone scenario) and assumes that the same energy is delivered. The smart charging methodology proposed follows the sequence depicted in Fig. 8 and it is composed by the following three steps:

1. *Get aggregated time series demand*: given a datetime sequence and a charging sessions data set, the demand profile of every user profile is obtained as a time series format.
2. *Obtain the setpoint (Optimization)*: according to user profiles' demand, renewable PV generation and optimization objective (e.g. peak shaving, grid balancing or both), a convex optimization is performed to obtain the best-case optimal demand profile for each user profile (i.e. user profiles' setpoints).
3. *Postpone sessions (rescheduling)*: original sessions of each profile are shifted from time slot to time slot in order to match, if possible, the corresponding setpoint.

5.2.1. *Aggregated demand*

Considering $S_{CHARGE(t,t+\Delta t)}$, all sessions that remain charging within the time interval $[t, t + \Delta t]$, and therefore satisfy Eqs. (12) and (13), then the aggregated power demand within the time interval $[t, t+\Delta t]$ is calculated with Eq. (14) where P_s is the charging power of a charging session. The aggregated time series demand is calculated then for each time slot considering a time resolution?t and a window of time T.

$$t \geqslant TCHS_s \tag{12}$$

$$[t, t + \Delta t] \leqslant TCHE_s \tag{13}$$

$$D_{(t,t+\Delta t)} = \sum_{s \in S_{CHARGE(t,t+\Delta t)}} P_s \tag{14}$$

5.2.2. Optimization

A quadratic optimization has been developed to obtain the optimal time series demand of each user profile. Though the procedure is general enough to deal with other objectives, the following two objectives are approached in this smart charging simulation:

1. Minimize peaks of demand, shifting demand from peak hours to valley periods.
2. Minimize grid balance, moving demand to hours with local solar generation.

The optimization is constrained to only the Postpone flexibility strategy (see Fig. 6) and and no grid parameters have been used as a constraint in this case. Future work will address other levels of flexibility such as energy or power modulation and the consideration of grid congestion and other constraints linked to geolocation of delivered flexibility, resulting in different aggregations. The objective function of this problem is presented in Eq. (15). See Table 3 for nomenclature definitions. The first term corresponds to the grid balance strategy, while the second term refers to peak shaving.

$$min \sum_{t=1}^{T} w_1 (S_t - L_t - O_t)^2 + w_2 (L_t + O_t)^2 \tag{15}$$

Constrained to Eqs. (16) and (17):

1. Total EV demand must remain the same:

$$\sum_{t=1}^{T} O_t \Delta t = E \tag{16}$$

2. Demand can only be shifted forwards, not backwards (Postpone strategy):

$$\sum_{t=1}^{U} O_t \Delta t \leqslant \sum_{t=1}^{U} V_t \Delta t \quad U = 1, 2, \dots, T \tag{17}$$

The formulation results in a quadratic problem with linear constraints. Thus, a convex optimization has been applied to the objective function using the CVXOPT Python package [34].

5.2.3. Postpone sessions

In a smart charging application, each charging point would have to decide whether to charge or not when a vehicle starts a new connection. Thus, some in-place computation will be required and in the case of postponing the vehicle's charging, a new schedule proposed by the charging system. Thus, as a more practical approach, rather than optimizing the aggregated user profile demand, the smart charging algorithm presents a new schedule for each charging session. In that sense, Algorithm 1 presented in this section takes an optimal aggregated demand (i.e. setpoint obtained from Eq. (15)) as a reference and postpones each required session to satisfy it, resulting in a modified sessions data set basically with shifted charging start times. Moreover, we have considered a parameter δ_{flex} to represent the percentage of people participating in the flexibility program (i.e. responsive users), since probably not all users will be enthusiasts about this charging system or they simply will be unable to participate on specific days.

Algorithm 1. Postpone charging sessions according to power time series setpoint, for a single user profile

Input : charging sessions schedule S, power setpoint time series O, time interval Δt, percentage of responsive users δ_{flex}
Output : modified schedule of charging sessions S

while *True* **do**
 Get L_t, total power demand timeseries from charging sessions
 Define T_{SHIFT}, a vector of time slot values where $L_t > O_t$
 if $length(T_{SHIFT}) = 0$ **then**
  break `/* No more flexibility required */`
 end
 $P_{SHIFT} = L_t(T_{SHIFT}) - O_t(T_{SHIFT})$ `/* power to shift in` T_{SHIFT} `time slots */`
 S_{FLEX} = sessions with potential to be shifted `/* i.e.` $TCHS_s = any(T_{SHIFT})$ `and` $F_s \geq \Delta t$ `*/`
 S'_{FLEX} = randomly select a percentage δ_{flex} from S_{FLEX}
 if $length(S'_{FLEX}) = 0$ **then**
  break `/* No more flexibility available */`
 end
 $TI = min(T_{SHIFT})$ `/* Time slot to shift sessions from */`
 S''_{FLEX} = sessions from S'_{FLEX} that start in TI
 Sort S''_{FLEX} from higher to lower F_s
 $PI = P_{SHIFT}(TI)$ `/* power to shift in` TI `time slot */`
 $s = 1$
 while $PI > 0$ *and* $s <= rows(S''_{FLEX})$ **do**
  <!– $s = S''_{FLEX}(s)$
  –> $TCHS_s = TCHS_s + \Delta t$ `/* Shift session a time slot */`
  $F_s = F_s - \Delta t$ `/* Reduce flexible time a time slot */`
  <!– $S(s_{id}) = s$ `/* Update original schedule with the modified session */`
  –> $PI = PI - P_s$ `/* Update the pending power to shift */`
  $s = s + 1$
 end
end

Table 4
Weights of optimization objectives.

Scenario	Profile	w1	w2
Without user profiles	-	0.5	0.5
With user profiles	Worktime	1	0
	Commuter	0	1

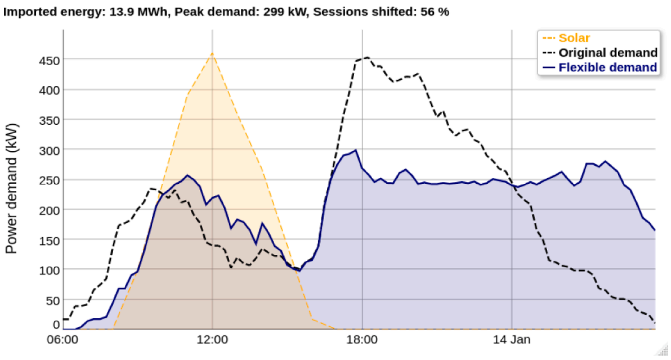

Fig. 9. Scenario 1: optimization without user profiles.

All these points of the algorithm are inside a `while(True)` loop structure that aims to iterate over all potentially flexible sessions (S_{FLEX}) in every time slot where flexibility is required, and leave the loop (i.e. `break` statement) when (1) there is no required flexibility (i.e. the demand setpoint is not surpassed in any time slot), or (2) there is no available flexibility (i.e. sessions have fully exploited their flexibility). Note that this algorithm considers only a Postpone smart charging strategy (see Fig. 6), and further development must take place if other strategies such as power modulation or dividing the session in shorter sessions are to be considered.

5.3. Smart charging simulation

This section proposes a scenario where the municipality of Arnhem aims to supply as much as possible the EV fleet with energy from a local PV field of 500 kWp (i.e. grid balancing minimization), maintaining the aggregated demand curve as flat as possible (i.e. peak shaving minimization). In this scenario, the EV aggregator should optimize the aggregated EV demand by rescheduling charging sessions for a specific time window. For this simulation, real EV sessions are used to decouple results from quality of forecasting. However, in both forecasting and scheduling problems, the knowledge about the existing EV user profiles would reduce the uncertainty since the problem is decomposed and analyzed separately. Thus, the objective of the methodology proposed here is to simplify the decision-making process of the aggregator in the optimization stage, where adjusting the parameters of individual sessions through a single tariff without differentiating the connection profile could be inefficient.

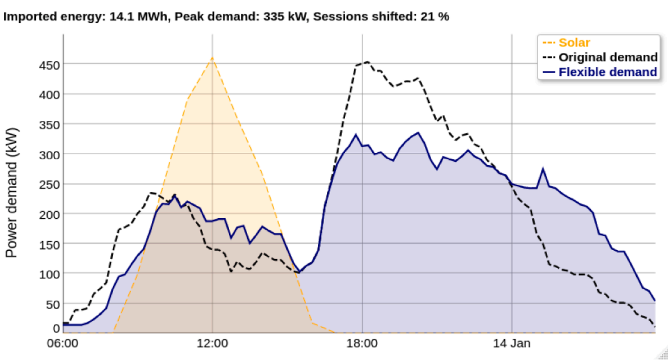

Fig. 10. Scenario 2: optimization with user profiles.

Table 5
Optimization results.

Optimization	Sessions shifted (%)	Reduction of peak demand (%)	Reduction of grid energy (%)
Without user profiles	56	34	6
With user profiles	21	26	5

The performance of optimizing a set of EV sessions with and without user profiles is compared by considering two different optimization objectives: evening peak shaving and grid balancing. According to these optimization objectives, and the flexibility potential of each user profile seen in Fig. 7, the profiles used for each optimization objective and their corresponding weights are described in Table 4.

Postponing all potentially flexible sessions without user profiles is a scenario constructed to show the best-case performance. Fig. 9 shows the result of combining the peak shaving and grid balancing optimization objectives (i.e. $\mathtt{w1} = 0.5$ and $\mathtt{w2} = 0.5$) and applying the postpone strategy. Postponing 56% of the total number of sessions, we can see a reduction in the peak demand of 155 kW, while the energy imported from the grid has been reduced by 218 kWh. On the other hand, Fig. 10 shows the result of addressing the peak shaving optimization with the Commuter profile (i.e. $\mathtt{w1} = 0$ and $\mathtt{w2} = 1$) and the grid balancing optimization with the Worktime profile (i.e. $\mathtt{w1} = 1$ and $\mathtt{w2} = 0$). In this case, only 21% of the sessions have been postponed, while the reduction in the peak demand has been 118 kW and the energy

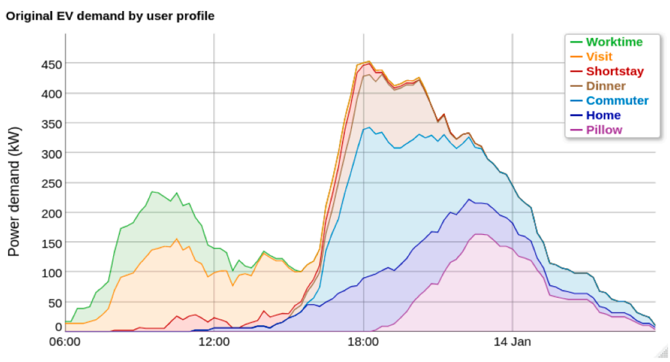

Fig. 11. Original EV power demand by user profile.

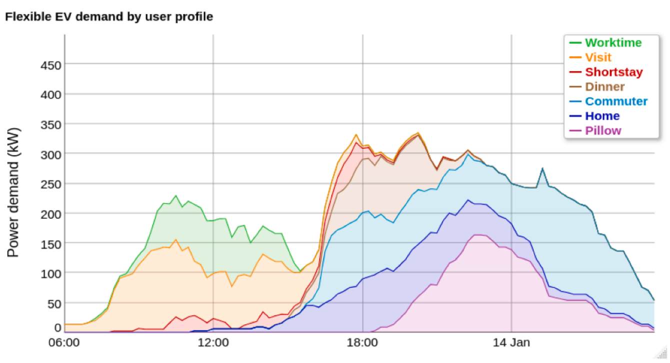

Fig. 12. EV power demand by user profile in Scenario 2.

imported from the grid has been reduced by 182 kWh. To compare both scenarios, Table 5 provides a summary of the results.

Obviously the best-case results are obtained shifting all potentially flexible sessions, independently of user profiles (i.e. business-as-usual case), since more sessions are available to postpone. However, the flexibility management based on user profiles resulted in a relevant improvement on the system efficiency, obtaining similar results than the best-case with practically a third part of the sessions. The optimization with user profiles has obtained 1% more imported energy, 8% higher peak demand and 35% fewer exploited sessions, which implies a relevant lower cost by the aggregator considering a compensation for each postponed session.

For a more in-depth analysis in the optimization with user profiles, Figs. 11 and 12 show the demand curves for each user profile before and after smart charging simulation, respectively. It is visible that early morning Worktime sessions have been shifted in order to charge as much as possible from solar generation, moving the peak to 11:00–12:00. At the same time, the pointed evening peak of Commuter sessions at 18:00–19:00 has evolved to a flatter curve shifting the demand to the night valley.

6. Conclusions

The first contribution this study makes is a methodology for characterizing EV charging sessions among generic user profiles, which has been validated with a real data set from the Dutch city of Arnhem. A first analysis of the relationship between the connection start time and connection duration of the sessions showed relevant covariance and multiple density peaks. These characteristics validated the use of bivariate Gaussian Mixture Models as a suitable clustering method. A posterior interpretation of each cluster resulted in seven different user profiles, some of them very specific (Worktime, Diner, Shortstay and Commuter) and other more general (Visit, Home and Pillow). Two main conclusions can be drawn from the flexibility potential quantification: (1) each user profile has its own flexibility potential peak and (2) considering a Postpone smart charging strategy, the time-resolution of the demand response program should not be lower than 30 min. Therefore, the second contribution this paper makes is a Postpone algorithm based on user profiles, with the possibility of configuring the appropriate optimization objective (i.e. grid balancing and peak shaving) to a particular user profile according to its flexibility potential. This approach has resulted more efficient in terms of flexibility management than the best-case scenario where all sessions are considered for the demand-response program. Even though the best-case optimization obtained better grid performance indicators (1% less imported energy and 8% lower demand peak), their differences in comparison with the optimization based on the Worktime and Commuter user profiles are not as relevant as the difference in the flexibility exploitation (35% fewer postponed sessions). Future research should consider designing different policies or market tariffs for each user profile in order to optimize the aggregator profit and the EV user compensation in a win–win scenario. Moreover, other smart charging strategies that differ from postpone should be considered in order to modulate the charging power or energy of sessions, and improve the flexibility management results.

Glossary

Acronym	Description
ADMM	Alternating Direction Method of Multipliers.
BIC	Bayesan Information Criterion.
DBSCAN	Density-based spatial clustering of applications with noise.
DSO	Distribution system operator.
EC	European Commission.
EM	Expectation–Maximization
EU	European Union.
EV	Electric vehicle.
GMM	Gaussian Mixture Models.
ID	Identificator
LP	Linear Programming.
MILP	Mixed-Integer Linear Programming.
MM	Mixture Models.
PSO	Particle Swarm Optimization.
QP	Quadratic Programming.
RES	Renewable energy sources.
RFID	Radio-frequency identification.
V2G	Vehicle-to-grid

CRediT authorship contribution statement

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

Declaration of Competing Interest

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

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Appendix A. Clustering resources

This appendix was included to show in detail some development steps of the methodology exposed is Section 3.

A.1. BIC analysis

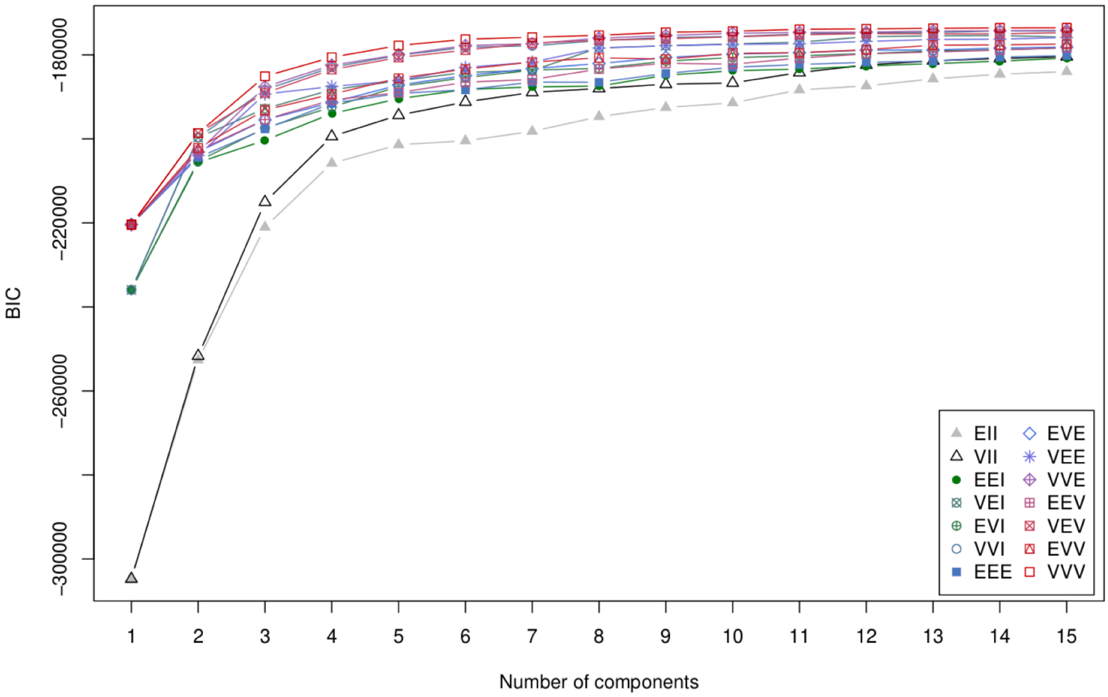

Fig. A.1. BIC analysis for weekdays city sessions.

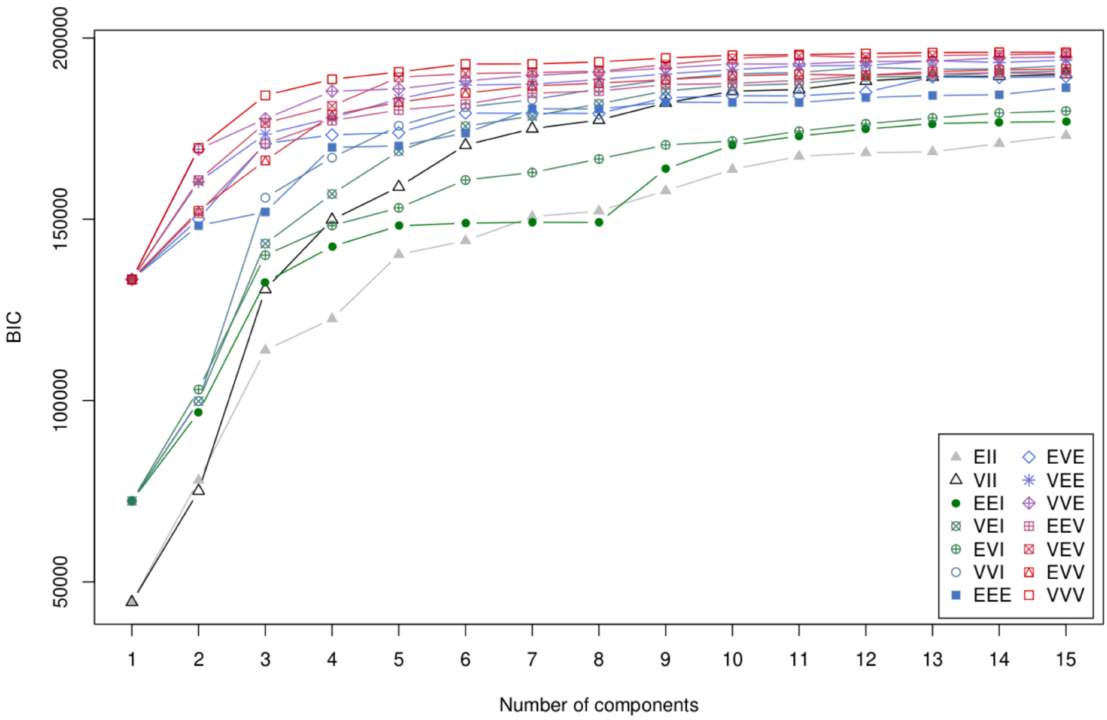

Fig. A.2. BIC analysis for weekdays home sessions.

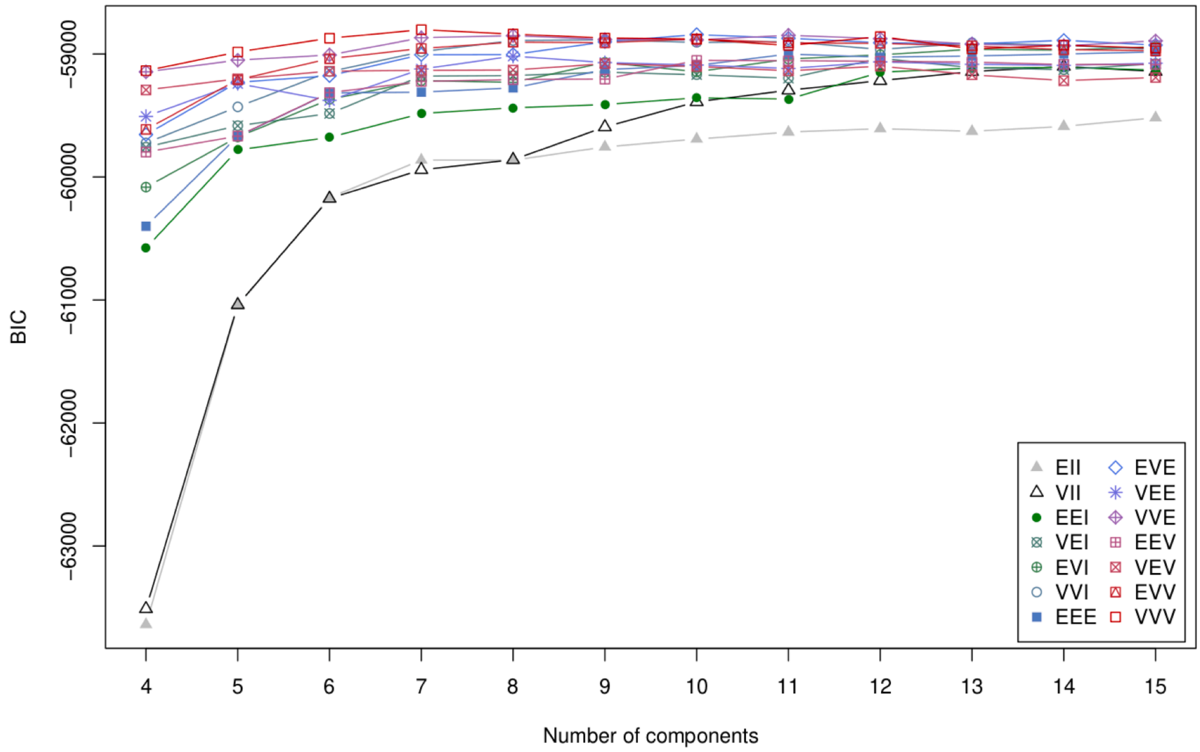

Fig. A.3. BIC analysis for weekends city sessions.

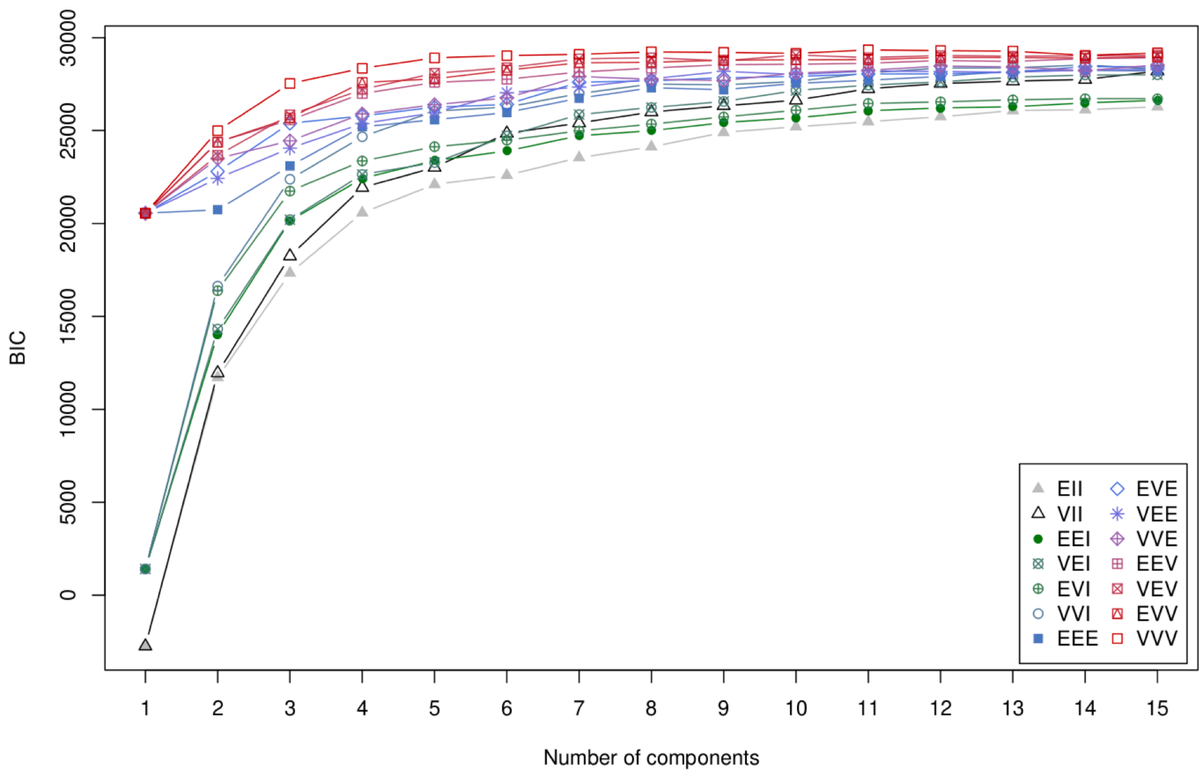

Fig. A.4. BIC analysis for weekends home sessions.

A.2. User profiles from clustering components

A.2.1. Weekdays city sessions

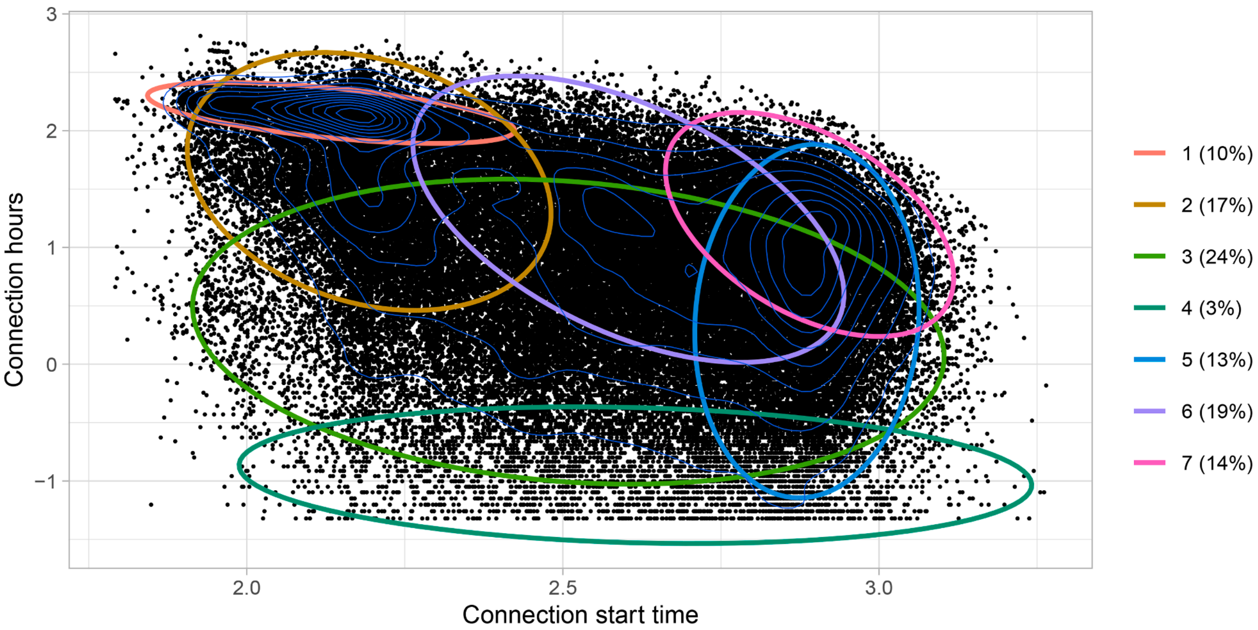

Fig. A.5. GMM clusters of weekdays city sessions.

Table A.1
Weekdays city clusters interpretation.

Cluster	Average start time	Average duration (h)	Interpretation	Profile
1	09:27	8.60	Full-day workers or visitors	Worktime
2	09:58	4.78	Visit the city during the morning	Visit
3	13:17	1.32	Short visits during the day	Shortstay
4	14:40	0.39	Super short connections during the day	Shortstay
5	18:55	1.45	Short visits during the evening	Shortstay
6	14:31	3.46	Visit the city during the afternoon	Visit
7	19:00	3.31	Go out for a dinner	Dinner

A.2.2. Weekdays home sessions

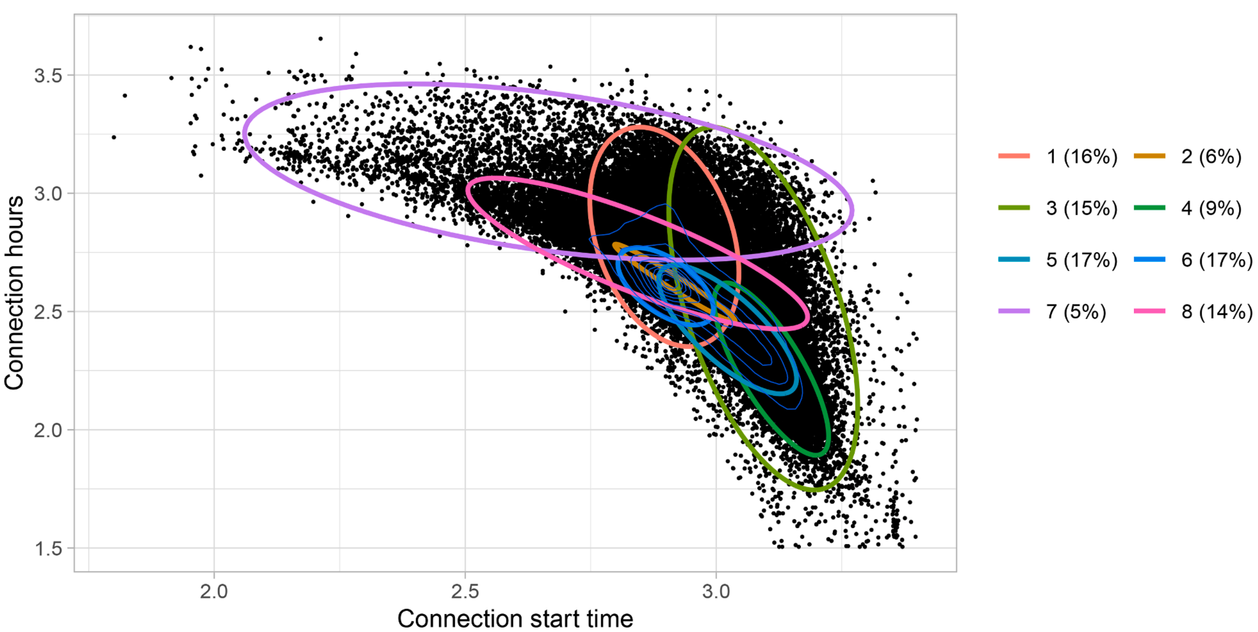

Fig. A.6. GMM clusters of weekdays home sessions.

Table A.2
Weekdays home clusters interpretation.

Cluster	Average start time	Average duration (h)	Interpretation	Profile
1	19:07	16.70	Go home during the afternoon, not necessarily leaving the next morning	Home
2	19:30	13.75	Always go home after work, always leaving the next morning	Commuter
3	23:04	12.33	Go home at night, not necessarily leaving the next morning	Pillow
4	23:25	9.55	Go home at late night, leaving the next morning	Pillow
5	21:33	11.29	Go home at night, leaving the next morning	Pillow
6	19:10	13.55	Always go home after work, always leaving the next morning	Commuter
7	15:23	21.97	Can go home anytime, not necessarily leaving the next morning	Home
8	18:11	15.57	Go home during the afternoon, leaving the next morning	Home

A.2.3. Weekends city sessions

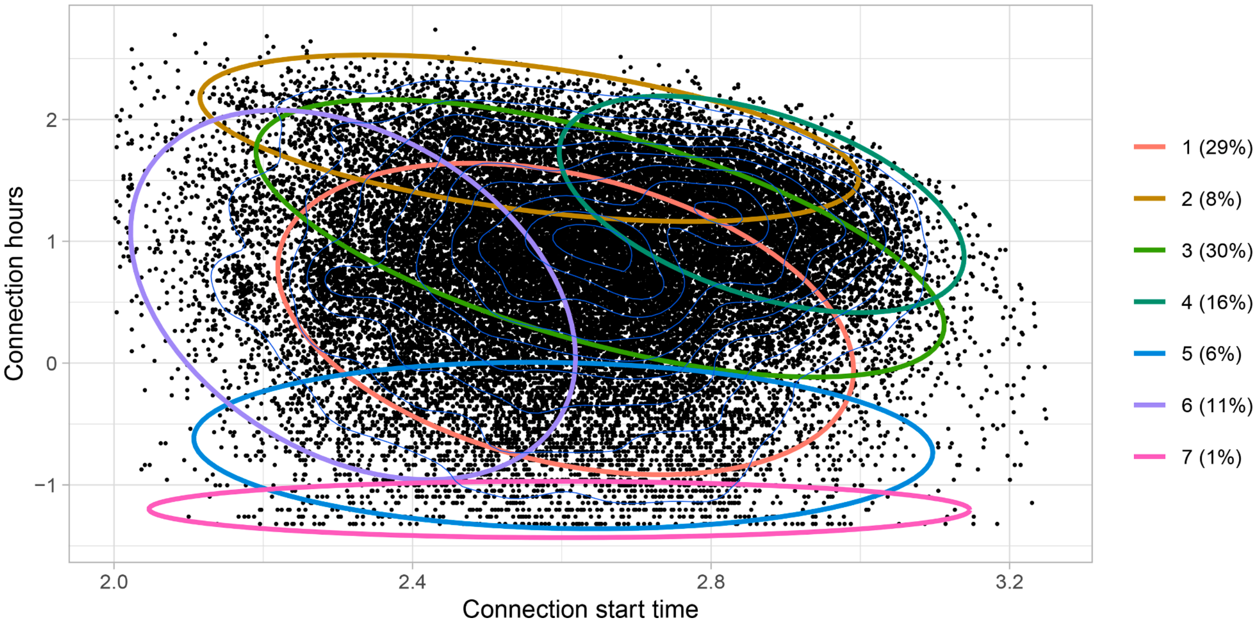

Fig. A.7. GMM clusters of weekends city sessions.

Table A.3
Weekends city clusters interpretation.

Cluster	Average start time	Average duration (h)	Interpretation	Profile
1	14:32	1.44	Short visits during the afternoon	Shortstay
2	13:53	6.34	Visit the city during the day	Visit
3	15:10	2.79	Visit the city during morning or afternoon	Visit
4	18:36	3.68	Go out during afternoon and probably dinner	Dinner
5	14:29	0.51	Super-short connections during the day	Shortstay
6	11:11	1.75	Short visits during the morning	Shortstay
7	14:25	0.30	Super-short connections during the day	Shortstay

A.2.4. Weekends home sessions

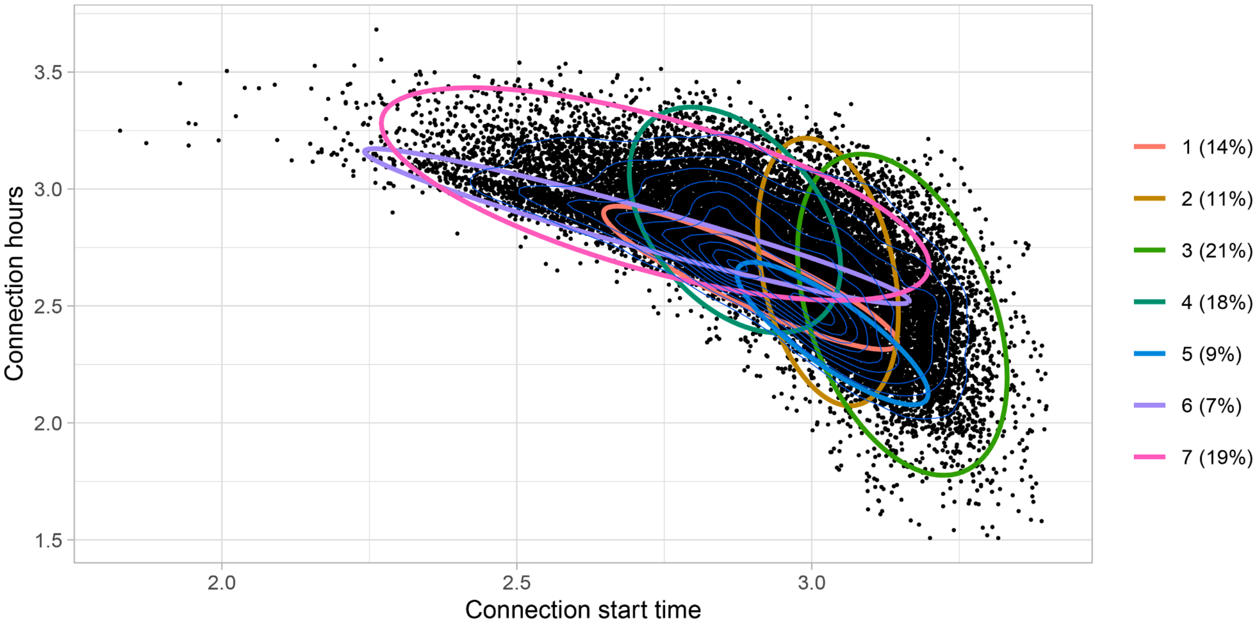

Fig. A.8. GMM clusters of weekends home sessions.

Table A.4
Weekends home clusters interpretation.

Cluster	Average start time	Average duration (h)	Interpretation	Profile
1	19:06	13.74	Go home at evening, normally leaving the next morning	Home
2	21:39	14.09	Go home at night, not necessarily leaving the next morning	Pillow
3	00:25	11.73	Go home at night, not necessarily leaving the next morning	Pillow
4	18:38	17.59	Go home during the evening, not necessarily leaving the next morning	Home
5	21:48	10.83	Go home at night, normally leaving the next morning	Pillow
6	15:56	17.13	Go home during the afternoon, normally leaving the next morning	Home
7	16:24	19.65	Go home during the afternoon, not necessarily leaving the next morning	Home

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Chapter 4

Assessment of electric vehicle charging hub based on stochastic models of user profiles

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ABSTRACT

A significant challenge in the electric mobility transition is the planning of proper charging infrastructures to incentivize the use of electric vehicles (EV) and guarantee a reliable charging service to EV users. This paper proposes to model generic EV user profiles (e.g. worktime, commuters, etc.) together with a simulation framework to appropriately assess charging hubs that become undersized due to growing EV demand. First, Gaussian Mixture Models (GMM) of different EV user profiles are developed in order to simulate multiple scenarios of EV sessions per day (N). Second, an algorithm is presented to simulate the occupancy of a charging hub based on two parameters: (1) the number of charging points (P) and (2) the connection time limit (H). Finally, the charging hub assessment is performed according to a metric designed to consider the interests of both the EV user and the charging hub operator, recommending the optimal P for expandable hubs, or the optimal H for limited hubs. Both cases are analysed in the validation section of this work employing a real-world use case. Results validate that the presented methodology can be used by EV charging hub operators to achieve a balance between the exploitation of the charging installation and the satisfaction of EV users.

1. Introduction

The electrification of the mobility sector is presented as an opportunity for the energy transition to build a greener and more sustainable power system. However, citizens may find multiple barriers when shifting towards electric vehicles (EV), such as economic (e.g. purchase price, electricity cost), technical (e.g. limited range, long charging time) or regulatory (e.g. absence of tax exemptions, lack of awareness about EV policies Munshi, Dhar, & Painuly, 2022) (Savari et al., 2023), being the lack of charging stations one of the most important barriers (Adhikari, Ghimire, Kim, Aryal, & Khadka, 2020). Current research shows that initial investments, by public or private entities, in charging infrastructure have an immediate positive effect on EV adoption (Kumar, Chakraborty, & Mandal, 2021) and this positive effect even increases over time (Delacrétaz, Lanz, & van Dijk, 2020). There is extensive literature dedicated to the placing (i.e. the best location and distribution) (Cao, Wan, Wang, & Wu, 2021; Liu, Zhang, Zhu and Ma, 2018; Quddus, Shahvari, Marufuzzaman, Eksioglu, & Castillo-Villar, 2021) and dimensioning (i.e. capacity and power connection) of future charging infrastructures from a distribution grid point of view, taking into account the existing road network (Mowry & Mallapragada, 2021; Quddus, Yavuz, Usher, & Marufuzzaman, 2019) or even integrating renewable energy sources (Nishanthy, Raja, Praveen, Nesamalar, & Venkatesh, 2022; Taghizad-Tavana, Alizadeh, Ghanbari-Ghalehjoughi, & Nojavan, 2023; Wahedi & Bicer, 2022). Also, there is a big focus on optimizing the cost of charging hubs and maximizing the investment return (Wahedi & Bicer, 2022; Wei et al., 2022; Zhou, Zhu, & Luo, 2022). However, the satisfaction of EV users with the charging service is usually ignored in the literature, even though the trust of EV users in the charging infrastructure and their acceptance as a reliable service is essential for the business model (Zhao, Fang, & Jin, 2018). Therefore, for the progressive adoption of EVs it is crucial to consider the expected behaviour of the EV users in the design process of charging hubs in order to meet their charging requirements while avoiding unnecessary costs and investments (Metais, Jouini, Perez, Berrada, & Suomalainen, 2022).

A charging hub can be oversized or undersized in comparison to its demand. An oversized charging hub has a constant high rate of empty charging points, supposing futile investments and higher exploitation costs (e.g. maintenance, grid connection tariff, space usage, etc.) that could harm the business model of the charging hub operator. On the other hand, an undersized charging hub could generate waiting queues and prevent some EV users from charging. This involves less energy sold and more users being unsatisfied with the charging service, which leads to a direct loss of potential clients. Given the expected growth

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of EV demand, this 'undersized' situation will be common and relevant for the existing charging hubs in a near future. Moreover, it is a natural trend to expand the existing EV charging hubs together with the EV demand since it represents a lower cost than building new ones (He, Kuo, & Sun, 2022). Therefore, given that the typology of EV users highly depends on the user habits and context (e.g. location of the charging hub, economic activity in the area, day of the week, seasonality, etc.), it is essential to establish methods for assessing saturated charging hubs from a user-centric approach to obtain the optimal solution for both the users and the charging hub operator.

In some works, the satisfaction of EV users is analysed and introduced in the planning equation to optimally allocate charging stations within a geographical area. In Liu et al. (2018), the satisfaction degree of EV users is quantified according to the time they need to find a charging station and fill the battery. Similarly, Liu, Zhang et al. (2018) and Xu, Pei, and Zhang (2022) describe EV user satisfaction degree as a percentage depending on the distance between the EV user location and the nearest charging station. These works simulate the EV demand with simple Probability Distribution Functions (PDF) to include stochasticity in the simulation. However, these distributions do not represent the multiple user behaviours or profiles that are present in real situations. Modelling these profiles is fundamental to accurately estimate EV demand peaks when planning infrastructures (Metais et al., 2022; Powell, Cezar, & Rajagopal, 2022), and using the connection variables (i.e. start time, end time and duration) is commonly considered in the literature to characterize connection patterns. Thus, the connection start and end times variables were used in Sadeghianpourhamami, Refa, Strobbe, and Develder (2018) with DBSCAN clustering to discover profiles of users charging at workplace, at home or parking-to-charge. Four different EV user behaviours were detected using K-means clustering in Xiong, Wang, Chu, and Gadh (2018) using connection start and end times, connection duration and energy charged. The connection start and connection duration variables were used in Bouhassani, Refa, Van Den Hoed, et al. (2019) to detect office chargers, home chargers and visitors using a heat map and specific thresholds in the variables. A multinomial logistic regression technique over the connection duration was used in Wolbertus, Kroesen, van den Hoed, and Chorus (2018) to classify sessions between stop&charge, park&charge, work & charge, home&charge and long sessions. A four-variable (session start time, connection duration, hours between sessions and distance between sessions) GMM was used in Helmus, Lees, and van den Hoed (2020) to discover multiple types of office, overnight and non-typical users. However, clustering methods like DBSCAN or heat maps do not capture the uncertainty associated with EV user behaviour and, since daily human behaviour depends on a lot of different factors, it is crucial to consider stochasticity. With this purpose, the use of Mixture Models (MM) is increasing in current literature to provide convenient representations for modelling complex distributions of data affected by random phenomena (McLachlan, Lee, & Rathnayake, 2019) in order to capture the uncertainty and stochasticity in charging demand (Powell et al., 2022). Moreover, MM also provide parametric information (location and spread) to characterize the different profiles associated with every cluster, avoiding further processing and modelling of clusters identified by non-parametric methods as K-Means (Xiong et al., 2018). Therefore, the use of MM is a convenient method to model EV user profiles based on the basic variables available from any charging infrastructure (i.e. connection start time, connection duration and energy charged) that allows modelling stochasticity and enables for simulation of realistic scenarios for planning charging hubs. This EV 'user profile' concept was first raised in Cañigueral and Meléndez (2021b), where a clustering methodology based on Gaussian Mixture Models (GMM) and Expectation–Maximization (EM) algorithm was used to group EV charging sessions into these daily connection patterns called user profiles (e.g. Worktime, Visitor, Commuter, etc.). The clustering methodology was then improved in Cañigueral and Meléndez (2021a) introducing DBSCAN clustering to clean outliers in a step previous to GMM clustering. Thus, this works aims to bring this clustering methodology a step further complementing it with modelling and simulation features, described in Section 2.1 and collected in two open-source R packages, `evprof` (Cañigueral, 2023a) and `evsim` (Cañigueral, 2023b), for better reproducibility.

Besides the optimal sizing problem, another possible situation that charging hub operators could face is the incapacity to expand the number of charging points. There are multiple reasons that could limit the charging hub expansion, for example, that the maximum allowed power grid connection is already contracted, zero budget for new investments or limited space for new chargers. In this scenario, it is convenient to regulate the EV connections with the objective of making the existing charging hub available for most users. Regulation of charging stations is commonly approached from a distribution grid's point of view, modifying the charging power to shave demand peaks (Bertolini, Martins, Vieira, & Sousa, 2022; Ravi & Aziz, 2022), maximizing the use of renewable energy (An et al., 2023; Bertolini et al., 2022; Kichou, Markvart, Wolf, Silvestre, & Chouder, 2022) or increasing the quality of power supply (Ahmed & Çelik, 2022; Çelik, 2022; Liu et al., 2023). In contrast, since this work is approached from the users' perspective, the regulation contemplated is focused on alleviating the occupancy of a charging hub limiting the connection time of the vehicles. This regulation measure is commonly used in undersized charging hubs, since it avoids having vehicles connected but not charging, ensuring that most vehicles have the same opportunities to charge. However, if the connection time is too short, most vehicles will not charge their required energy and they will not be satisfied either. In these cases, a charging hub could be optimally sized but badly regulated. Therefore, when regulating the users' activity it is very important to first perform a user behaviour analysis since the regulation can affect each user typology differently (e.g. users with work are more sensitive to parking regulation Simićević, Vukanović, & Milosavljević, 2013). In that sense, the assessment methodology proposed in this work uses the extra knowledge about user behaviour obtained during the modelling process to optimally set connection limits according to users' needs and flexibility.

Together, this work proposes a framework to simulate the activity of EV charging sessions in a charging hub, in order to maximize the interests of EV users and charging hub operators in two relevant scenarios: (1) optimal sizing of a charging hub that can be expanded and (2) optimal connection limit for a limited charging hub.

Section 2 describes the modelling and simulation methodology proposed, together with the custom indicators designed to quantify the performance of the charging hub from both user and charging hub operator perspectives. This methodology is validated in Section 3 with a real data set of charging sessions and the results are discussed in Section 4. Finally, Section 5 concludes with the main outcomes of this paper and further work.

2. Methodology

This section presents the methodology developed in order to assess charging hub operators in terms of optimal size (i.e. number of charging points P) and optimal regulation (i.e. connection time limit H). To obtain these values, it is necessary to simulate the expected EV charging sessions and their interaction with the charging hub at issue. The full methodology is summarized in the following points, and further described in the following subsections:

1. Development of stochastic models of charging sessions. The models are created from real data sets of charging sessions using Gaussian Mixture Models (GMM). The methodology is collected in the `evprof` open-source R package (Cañigueral, 2023a).

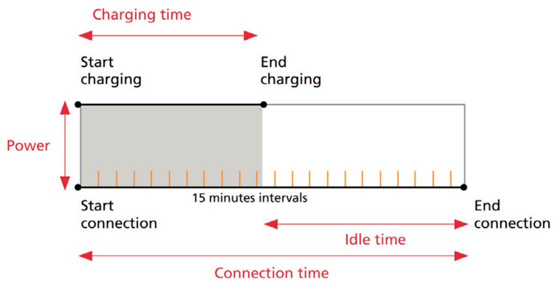

Fig. 1. Parameters of a charging session.
Source: HvA (van den Hoed et al., 2019).

2. Simulation of charging sessions. The GMM are used to simulate different scenarios of EV demand, based on the number of charging sessions per day (N) and the day of the week. The methodology is collected in the `evsim` open-source R package (Cañigueral, 2023b).
3. Simulation of charging hub occupancy. The demand of EV users in a charging hub with a specific number of charging points (P) and connection time limit (H) is simulated.
4. Assessment of the charging hub. The simulations of different combinations of N, P and H let to quantify the charging hub performance with a $ChargingHappiness$ metric designed for this purpose.

2.1. Charging sessions models

Charging sessions can be characterized by three parameters: connection time, charging time and charging power (van den Hoed et al., 2019). The connection time is the time that the EV remains connected to the charging station while the charging time only considers the time the vehicle is charging. The charging time is usually lower than the connection time as illustrated in Fig. 1. For simplicity, the charging power profile is considered to be a step of constant power that depends on the charging station and the EV model and lasts until the battery is filled or the vehicle is disconnected.

However, the charging time depends on the energy required by the user and the charging power of the session. The only variables that are inherited from the EV user itself and do not depend on the study case are the connection times (which depend mostly on the user's timetable) and the energy required (related to the user's journey). Therefore, this work presents the charging sessions' models as a combination of connection models and energy models. The modelling methodology presented in this paper extends the previous work done in Cañigueral and Meléndez (2021a, 2021b), where a methodology for classifying charging sessions into generic EV user profiles (i.e. daily connection patterns) is described. This paper shows the added value of modelling these user profiles to simulate future scenarios of EV demand from a data-driven perspective.

This profiling process previously raised in Cañigueral and Meléndez (2021a, 2021b) submits a charging sessions data set into a Gaussian Mixture Models (GMM) clustering with the Expectation–Maximization algorithm (Fraley & Raftery, 2002), considering as clustering variables the connection start time (from 0 to 24) and the connection duration (in hours). Before the clustering process, the full data set of sessions is divided into smaller subsets (e.g. day/night sessions, working days/weekends, etc.) to increase the clustering performance. Finally, the clusters found are grouped into daily user profiles (e.g. worktime, commuters, etc.) to simplify the interpretation of the clusters while keeping the accuracy of the Gaussian models. One of the advantages of this clustering method is that, in addition to the classification, it provides the bi-variate (i.e. connection start time and duration) Gaussian model for every cluster. Thus, this paper brings further the previous profiling methodology adding a modelling step to stochastically simulate new EV connections.

Once different EV user profiles have been defined in terms of connection patterns, the modelling process is completed with the energy models. Each user profile must have a different energy model since the users with a shorter connection pattern (e.g. the dinner pattern from 18:00–22:00) have, in general, lower energy consumption than longer connection patterns (e.g. night connection from 19:00–7:00). Therefore, a density-estimation of the energy values from all sessions belonging to each user profile is performed, resulting in a mixture of Gaussian models for every user profile. The programming tool chosen to develop this modelling task is the R package `mclust` (Scrucca, Fop, Murphy, & Adrian, 2016).

In summary, every EV user profile discovered from existing representative data sets is modelled with (1) a combination of bi-variate GMM to estimate the connection start time and connection duration, and (2) a combination of uni-variate GMM to estimate the energy required by the charging sessions. This modelling methodology is collected under the open-source R package `evprof` (Cañigueral, 2023a), developed with the aim to be applicable to data gathered from different campaigns (e.g. existing charging infrastructures, smart sensors in parking slots, access control in parking or even manually collected during a period of time). Additionally, the models of EV user profiles previously built for a specific use case, for example Tables 1 and 2 of Section 3.1), could be used in future works to directly simulate new charging sessions instead of building dedicated models. However, for more accurate results, the use of data from similar existing charging hubs is recommended. The next section exposes how these models are used to simulate new charging sessions for a specific scenario.

2.2. Simulation of charging sessions

As raised in the previous section, the essential parameters to characterize a charging session are the connection times, the energy required and the charging power.

The values of connection times and the energy required for a new set of charging sessions can be simulated using Gaussian models of the user profiles, built according to the methodology in Section 2.1. On one hand, the connection models are bi-variate Gaussian models so the inputs to simulate new data points are the number of observations, the means of the variables (μ) and the covariance matrix (Σ). The new observations are estimated with the function `mvrnorm` of the R package `MASS` (Venables & Ripley, 2002). On the other hand, the energy models are Gaussian models of a single variable, so the inputs to simulate new data points are the number of observations, the mean (μ) and the standard deviation (σ). The new observations are estimated with the function `rnorm` of the R package `stats` (R Core Team, 2013).

However the relevance of a user profile and the number of charging sessions are variables that depend on the day of the week, the month of the year or even the season, and these can be changed at the simulation stage to be representative of specific case studies (i.e rising EV deployment, change of daily habits, special events, etc.). Thus, the number of sessions per day (N) and the share (i.e. weight) of each user profile can be adjusted for every day in the simulated period to be representative of specific scenarios and provide realistic simulations. For example, the number of sessions per day on a Monday can be $N = 10$ with a user profiles' distribution of $Workers = 80\%$ and $Visitors = 20\%$, while on a Saturday it could be $N = 8$ with $Workers = 10\%$ and $Visitors = 90\%$. Thus, the simulation algorithm must first check the day of the week to simulate and then the corresponding configuration of sessions per day and the share of the user profiles. This example could be extrapolated to different time cycles such as the month of the year and, if the data set is large enough, the Gaussian models of the user profiles could be different for every time cycle as well (e.g. Workers-Summer, Workers-Winter, etc.).

Input : Schedule of charging sessions S, number of charging points P, maximum connection hours H
Output: Modified schedule of charging sessions S

1 Limit the $ConnectionHours$ and $ChargingHours$ of all sessions up to H
2 $ConnectionEndDateTime = ConnectionStartDateTime + ConnectionHours$ `// Update connection end time`
3 $ChargingEndDateTime = ChargingStartDateTime + ChargingHours$ `// Update charging end time`
4 Get $dttmSeq$, the date-time sequence between the minimum connection start value and the maximum connection end value from sessions, with a time resolution of 15 minutes
5 Get $nConnections$, a vector with the number of vehicles connected at the same time, for every value of $dttmSeq$
6 Get $dttmSeqFull$, the values of $dttmSeq$ when $nConnections > P$ `// Select the time slots with full occupancy`
`/* Don't charge sessions that start at a time slot with full occupancy */`
7 **for** i *in* 1 *to* $length(dttmSeqFull)$ **do**
8 $\quad ConnectionEndDateTime = ConnectionStartDateTime$ for sessions that start in $dttmSeqFull[i]$
$\quad ChargingEndDateTime = ChargingStartDateTime$ for sessions that start in $dttmSeqFull[i]$
9 **end**
`/* Include in S the new value of energy charged with time limitation */`
10 $EnergyCharged = (ChargingEndDateTime - ChargingStartDateTime) * Power$

Algorithm 1: Algorithm to simulate EV charging

Finally, once the connection times and energy variables are estimated, a charging power value has to be added to the charging session. This methodology distinguishes the charging power from the connection and energy models so as to be usable in a wide variety of study cases. For example, the charging points of the parking in public charging infrastructure allow a maximum power of 11 kW, while the charging hubs in supermarkets or companies allow normally low charging powers (such as 3.7 kW) to provide a service to clients without compromising the power connection to the grid. For this work, the minimum charging power that is accepted by all EV models (3.7 kW) has been assigned to all sessions. Other approaches could be the nominal power of the charging stations, the average of the market EV models or a custom power distribution found from a real data set. This EV simulation methodology is collected in the open-source R package `evsim` (Cañigueral, 2023b), which is directly related to the EV models built with package `evprof` (Cañigueral, 2023a).

2.3. Charging hub occupancy

Limiting the connection time of the sessions is a direct and common strategy to ensure the maximum number of connections when a charging hub is saturated or undersized but, at the same time, it limits the energy that the vehicles can charge. To simulate the consequences of this charging hub regulation, Algorithm 1 modifies the connection and charging times of the sessions from a schedule S (see Table 3 in Section 3.2 for an example of schedule) according to the maximum connection hours H (lines 1–3 of Algorithm 1). Moreover, when the number of sessions connected simultaneously is higher than the number of charging points P, the simulator does not admit new connections and consequently, the sessions connecting in the next time slot are not considered (lines 7–9 of Algorithm 1). A new variable, $EnergyCharged$, is included in the schedule to differentiate the energy that the vehicle can finally charge during the assigned connection time from the energy that the vehicle originally required ($EnergyRequired$). The algorithm assumes that the connection limitation is totally effective (all users respect the regulation) so after a limited session the charging point is ready for a new connection.

Finally, the algorithm returns a table with the scheduled charging sessions considering the connection limitation. In this new schedule, sessions that find no available slots when they try to connect are ignored, so the charging station loses clients, and sessions longer than the maximum connection time H are shortened.

2.4. Charging hub assessment

Whether a charging hub is properly sized or not can be defined from different perspectives. From the charging hub operator's point of view, it will be optimal when the maximum amount of energy is sold with the minimum investment or exploitation costs. At the same time, EV users want to find a charging point available when they arrive at the charging hub and charge all their energy requirements.

On one hand, if more charging points than EV users are installed, everybody will be able to fill the battery (good for EV users and charging hub operators) but a high investment will be required as well as a high power grid connection cost (bad for charging hub operators' business case). On the other hand, when a charging station reaches its saturation point (i.e. more vehicles arriving than charging points available), the later sessions cannot connect, producing certain dissatisfaction for the users. In this saturation scenario, limiting the connection time of charging sessions is presented as a solution to maximize the charging hub performance by increasing the number of charging sessions able to connect. However, if the maximum connection time is lower than the desired charging time, user satisfaction is also affected and this can have consequences on their confidence in the charging service (i.e. loss of clients). Thus, in order to find a balanced solution from both perspectives, this section proposes a set of metrics to analyse the performance of a charging hub and its users' satisfaction. These metrics are defined by Eqs. (1), (2) and (3).

The term S represents the total number of sessions in the simulated schedule, while $FailedSessions$ is the number of sessions that cannot connect. The term $EnergyCharged$ refers to the energy that the user can charge within the connection time, while $EnergyRequired$ is the total energy that the user needs to completely fill the battery. The $ConnectionSuccess$ metric of Eq. (1) reflects the percentage of sessions that find an empty station and can connect the vehicle. The percentage of the total energy required by the vehicles that has been finally charged is reflected by the $EnergyFill$ metric of Eq. (2).

$$ConnectionSuccess = 1 - \frac{FailedSessions}{S} \tag{1}$$

$$EnergyFill = \frac{EnergyCharged}{EnergyRequired} \tag{2}$$

While $EnergyFill$ represents the interests of charging hub operators (income from energy sold), it does not ensure acceptable situations for EV users. An average value of $EnergyFill = 0.5$ will not differentiate between charging only 50% of sessions or charging 50% of all sessions' requirements, the latter being the preferred approach for the users' community. Therefore, a global $ChargingHappiness$ metric, shown in Eq. (3), is created to reflect the general satisfaction of both stakeholders, being a weighted average between $ConnectionSuccess$ and $EnergyFill$ metrics. The value of the weighting parameter q in Eq. (3) must be defined according to the objective of EV users in the use case at issue, but a default value of $q = 0.5$ could be representative of most cases. For example, in charging hubs where the objective is to park the vehicle rather than charge, the $ChargingHappiness$ should prioritize the $ConnectionSuccess$ over $EnergyFill$, setting a value of q higher than 0.5 ($q > 0.5$). Therefore, this metric is designed in such a manner that each of its parameters captures a distinct deficiency at the charging hub, from the EV user or the charging hub operator's point of view, and for a wide variety of scenarios. The interpretation of this metric is direct: the higher the $ChargingHappiness$, the better the solution.

$$ChargingHappiness = q \times ConnectionSuccess + (1 - q) \times EnergyFill \qquad q \in [0, 1] \tag{3}$$

Thus, it is possible to associate the possible situations of a charging hub, previously described in Section 1, with metrics from Eqs. (1), (2) and (3):

- Oversized charging hub: In these situations, the number of $FailedSessions$ is equal to zero, so the $ConnectionSuccess$ is maximum, and $EnergyFill$ is also maximum as all the cars can charge as long as they want. However, it is also possible that other scenarios with lower charging points (P) can provide the same quality of service.
- Undersized charging hub: In this situation, the number of $FailedSessions$ increases, according to how undersized the station is. Thus, the $ConnectionSuccess$ and the average $EnergyFill$ ratio will be lower than in other scenarios with the same number of sessions (N) and a more appropriate number of charging slots (P).
- Properly sized but badly regulated: Understanding the regulation as the introduction of a maximum value of connection hours (H), the number of $FailedSessions$ increases with too high values of H and the $EnergyFill$ ratio decreases if H is too low.
- Properly sized and properly regulated: In this situation, the number of $FailedSessions$ is zero or close to zero and the $EnergyFill$ ratio is the maximum or has an acceptable value. Compared with an oversized charging hub, in this scenario the infrastructure is the minimum required to achieve the optimal results.

The aim of this work is to assess charging hubs in any of the four situations described above, finding the best configuration of P and H for a given N:

- Optimal value of P: the minimum number of charging points for less investment, maintenance, power connection cost and space usage. This optimal value provides a certain level of $ChargingHappiness$ (e.g. 95%) given a scenario with specific N and H, even considering no connection limit (i.e. $H = \infty$).
- Optimal value of H: the limit of connection time that provides the maximum $ChargingHappiness$ given specific values of N and P.

3. Calculations

The methodology presented in Section 2 has been validated with a real data set of charging sessions from the Borg Harbour, the Norwegian pilot in the H2020 E-LAND project (Eland, 2020). The current number of charging points in the pilot is $P = 8$. The original data set consists of 1807 sessions from 15 April 2019 to 4 May 2021, with an average of four sessions per day during working days and two sessions per day during the weekends. The charging sessions are described by the connection start/end times, the total energy charged and the identifier of the charging point in the charging hub. To perform the assessment of this charging hub, multiple scenarios have been simulated according to different values of the number of sessions per day (N) in a range from 1 to 24, the number of charging points (P) in a range from 1 to 25, and maximum connection hours (H) in a range from 1 to 24. The ranges of parameters N, P and H have been selected in this work in a realistic range for the charging station under study; however, they can be redefined for other case studies accordingly. For every combination of these three parameters, one month of sessions and the corresponding occupancy have been simulated using Algorithm 1 from Section 2.3. These calculations resulted in a table with the metrics described in Section 2.4 of the 29.400 observations, which is not included in the paper due to space limitations.

3.1. Charging sessions model

The Borg harbour's charging sessions data set has been submitted to the clustering and modelling methodology exposed in Section 2.1, to model generic EV user profiles. Every user profile is modelled by Gaussian Mixture Models (GMM), considering both connection models (to estimate the connection start time and connection duration) and energy models (to estimate the energy required by the charging sessions). The two types of models are presented in the next subsections.

3.1.1. Connection models

The data set has been divided into two subsets to discriminate between day and night sessions. Clustering each subset separately has been demonstrated to increase the quality of the models obtained, with greater separation among clusters and lower variance of models. In total, ten different clusters have been obtained: seven for day-sessions and three for night sessions. Fig. 2 shows the clusters for the day sessions. Each session is represented by a point in the coordinates defined by the connection start and duration, in both hours and logarithmic scale. Each cluster is represented with an ellipse, with a centroid as the average value of the two clustering variables (i.e. connection start hour and connection hours) and a shape corresponding to the variability in both variables.

In the second stage of this modelling process, the ten clusters have been mapped with seven user profiles that describe common charging habits, being Worktime, Morning, LateMorning, Short, Evening, Night and Long profiles. The user profiles' names have been created according to the connection pattern related to the centroid of the clusters, i.e. average values of connection start time and connection duration. The final classification of all charging sessions in the corresponding user profiles is shown in Fig. 3. The parameters of the associated bivariate Gaussian models of every user profile are listed in Table 1. Note that the values are in logarithmic scale. The combination of several clusters into the same user profile aims to use Gaussian Models to represent arbitrary user patterns. When several clusters define a connection pattern, the parameter $Share$ defines the percentage of sessions corresponding to each cluster (see column $Share$ of Table 1).

3.1.2. Energy models

The user profiles models have been completed with the corresponding energy models. Again, a density estimation via model-based clustering has been used to obtain the Gaussian Mixture Models of the energy values from all sessions corresponding to every user profile. Table 2 reports the mean (μ), variance (σ^2) and share of sessions (i.e. ratio of sessions within the same user profile) of the Gaussian Models that compose every user pattern.

More visually, Fig. 4 shows the density values histogram in grey and the density distribution from the mixture of Gaussian Models in blue. Some thin peaks stand out from these blue density curves, corresponding to Gaussian components with very small variance.

Table 1
Parameters of connection models (bivariate GMM).

User profile	Centroid (μ)	Covariance (σ)		Share (%)
Worktime	1.759762 2.064402	0.001289 −0.000522	−0.000522 0.002631	32
	1.918508 2.077859	0.001666 −0.00022	−0.00022 0.002231	45
	1.623326 2.229649	0.00527 −0.000347	−0.000347 0.006162	23
Morning	1.817562 1.571141	0.019075 −0.017767	−0.017767 0.064764	43
	1.899188 1.951741	0.009977 −0.003488	−0.003488 0.018946	57
LateMorning	2.287319 1.388538	0.02093 −0.043299	−0.043299 0.132277	100
Short	1.890992 0.91952	0.040457 0.001292	0.001292 0.037134	100
Evening	2.777012 1.414201	0.062041 −0.042358	−0.042358 0.138383	100
Night	2.804282 2.571152	0.062041 −0.042358	−0.042358 0.138383	100
Long	2.788976 3.40463	0.062041 −0.042358	−0.042358 0.138383	100

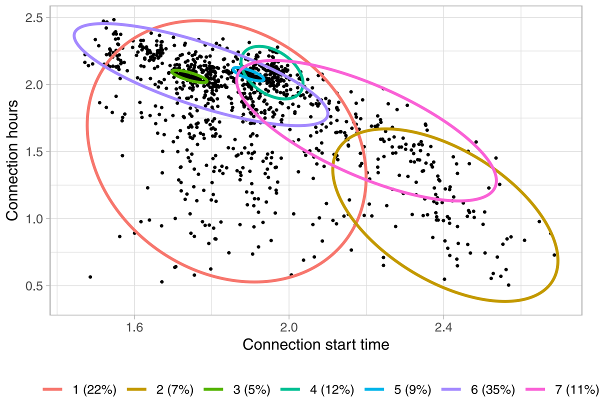

Fig. 2. Cluster for different day-sessions.

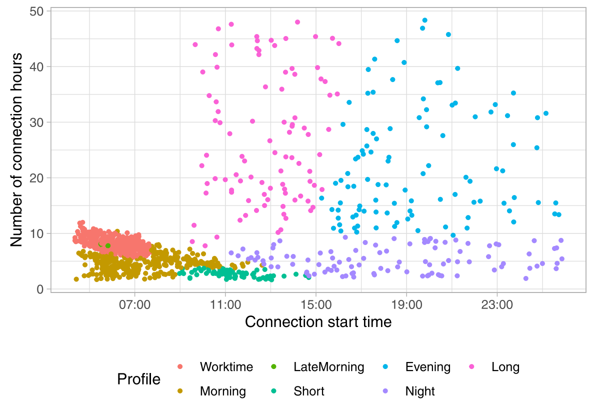

Fig. 3. Final sessions' classification among user profiles.

Table 2
Parameters of energy models (univariate GMM).

User profile	Mean (μ)	Variance (σ^2)	Share (%)
Worktime	1.495388 2.192015 2.332631 3.545547	0.024106 0.000967 0.104584 0.049427	11 18 57 14
Morning	2.26716 2.188486 3.39525	0.283973 0.000327 0.005033	85 9 7
LateMorning	2.05725 2.19717 2.37154 3.77877	0.102903 0.000309 0.000175 0.028681	52 16 15 17
Short	1.020958 2.258453	0.96175 0.170339	24 76
Evening	2.740724	0.140788	100
Night	2.772266	0.16829	100
Long	2.667698	0.208375	100

3.2. Charging sessions simulation

The simulated scenarios consist of the interaction between a determined number of EV users that want to park and charge their vehicles in a defined charging hub. Thus, different sets of sessions have been simulated according to a specific number of sessions per day (N).

The charging sessions have been simulated using the connection models from Table 1 and energy models from Table 2. This simulation has been done using the current share of sessions between user profiles depending on the day of the week as illustrated in Fig. 5. For this case study, no significant differences in the proportion of user profiles have been observed between months or seasons. Thus, the only discriminatory variable to simulate new charging sessions is the day of the week. Note that the Worktime profile is the most relevant one from Monday to Friday. Meanwhile, the Evening and Night profiles and Long sessions appear mainly during the weekend. Besides the user profiles distribution, the number of sessions per day is also different according to the day of the week. For this case study, the average number of sessions per day during weekends is half that of working days, so the simulations of other scenarios have considered this relation as well using N as the working days daily sessions, and $N/2$ as the weekend daily sessions.

Since available data does not contain power information, a charging power of 3.7 kW (single-phase 240 V 16 A) has been assumed for all sessions. This power rate is accepted by all EV models. Moreover, charging at 3.7 kW is considered the worst case from the infrastructure performance point of view, since it results in longer sessions and higher occupancy of the charging stations.

Table 3 shows an example of six simulated sessions obtained from the connection and energy stochastic models, defining every session's connection times, the charging power in kW, the energy required in kWh and the number of hours of connection and charging. The simulator can limit the $EnergyRequired$ according to the maximum possible energy charged within the corresponding $ConnectionHours$ and $Power$ values. Then, $ChargingHours$ is calculated by dividing the $EnergyRequired$ by the charging $Power$. Other variables calculated during the simulation from the variables in Table 3 are $ConnectionEndDateTime$, $ChargingStartDateTime$ and $ChargingEndDateTime$, which are then used in Algorithm 1.

3.3. Charging hub occupancy

The algorithm presented in Section 2.3 simulates the interaction of N charging sessions with a pre-defined charging hub with P charging points and regulated with a maximum connection time of H hours.

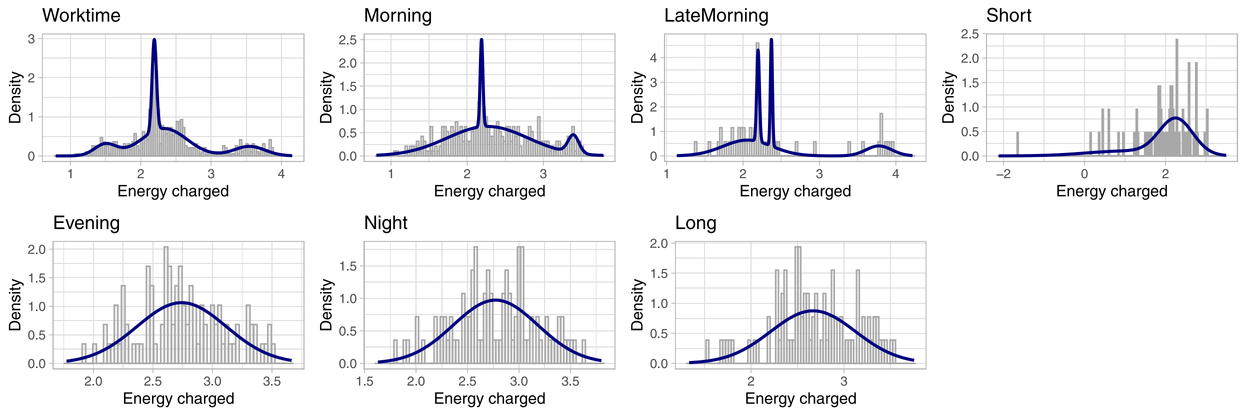

Fig. 4. Density values histogram and the density distribution from the Gaussian models.

Table 3
Example of a simulated scheduling of EV sessions.

Profile	Session	ConnectionStartDateTime	Power	EnergyRequired	ConnectionHours	ChargingHours
Worktime	S1	2021-02-01 05:30:00	3.7	12.950	9.00	3.50
Morning	S2	2021-02-01 06:15:00	3.7	10.175	2.75	2.75
Worktime	S3	2021-02-01 06:15:00	3.7	11.100	7.50	3.00
Worktime	S4	2021-02-01 06:30:00	3.7	9.250	8.25	2.50
Worktime	S5	2021-02-01 06:45:00	3.7	3.700	8.25	1.00
Morning	S6	2021-02-01 09:30:00	3.7	9.250	7.25	2.50

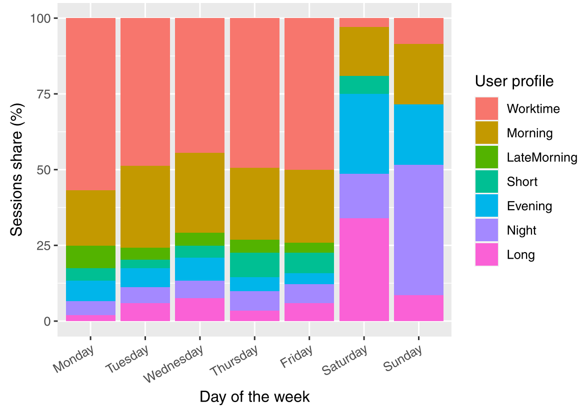

Fig. 5. Share of user profiles by day of the week.

An example of this occupancy simulation with $N = 15$ and $P = 8$ is shown in Fig. 6, comparing the number of connected vehicles that would be connected without any regulation ($H = \infty$) and limiting the connection time to 4 h. Without regulation (green line), the number of connected vehicles is usually higher than the regulation scenario. However, a connected vehicle is not necessarily charging and occupies a charging point that could be used for a future session. Thus, higher occupancy of the regulated scenario (blue line) than the non-regulated one means the avoidance of losing sessions.

4. Results and discussion

The calculations performed in Section 3 resulted in a table of 29.400 observations (not included due to space limitations), considering different values of the number of sessions per day (N) in a range from 1 to 24, the number of charging points (P) in a range from 1 to 25, the maximum connection hours (H) in a range from 1 to 24, and the corresponding metrics $ConnectionSuccess$, $EnergyFill$ and $ChargingHappiness$, described in Section 2.4. The weighting parameter q in Eq. (3) has been set to 0.5 in order to represent a balance between the interests of the charging hub operator and the EV user profiles. The analysis performed out of this table with all scenarios of N, H and P is used to find the best configuration of P and H for a given N, in order to assess charging hubs that are (or will be) undersized for the expected EV demand. Section 2.4 describes when values of P and H are optimal from a theoretic point of view, while this section aims to illustrate and validate the assessment with real data.

First, an exploratory analysis of the metrics obtained is developed in order to have a general overview of the charging hub assessment. Second, a real study case is used to raise two possible approaches to increase the performance of an undersized charging hub: (1) finding the optimal connection time limit (H) and (2) finding the optimal number of charging points (P).

4.1. Evolution of metrics according to N, P and H

A charging hub which is oversized, so with $P > N$, will always provide 100% of $ChargingHappiness$. This effect is illustrated in Fig. 7, where the $ChargingHappiness$ reaches its maximum when $P \geq N$, considering a connection limit of 24 h ($H = 24$). However, from an optimization perspective, it would be interesting to find a configuration that is slightly oversized to allow N to grow in the future or even undersize the charging hub to lower the power grid connection and other exploitation costs without compromising user satisfaction.

Expanding the number of charging stations in the charging hub could not always be a valid option due to space, power connection or budget limitations. In those cases, introducing a connection time limit (H) is a solution to increase the charging hub usage among EV users when $P < N$. In that sense, Fig. 8 shows that, considering a connection limit of five hours ($H = 5$), reasonably high values of $ChargingHappiness$ can be achieved given ten sessions per day ($N = 10$) and only seven charging points ($P = 7$). However, a limit of $H = 2$ would imply a too-short connection time that decreases the $EnergyFill$ metric and, consequently, the average $ChargingHappiness$. This effect is also visible in Fig. 9, where low H values give high

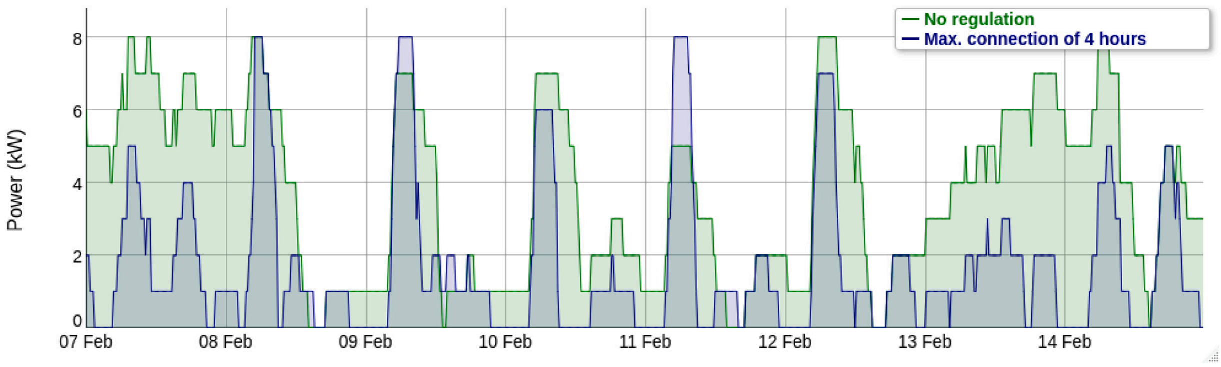

Fig. 6. Example of occupancy simulation without regulation (green) and $H = 4$ h (blue).

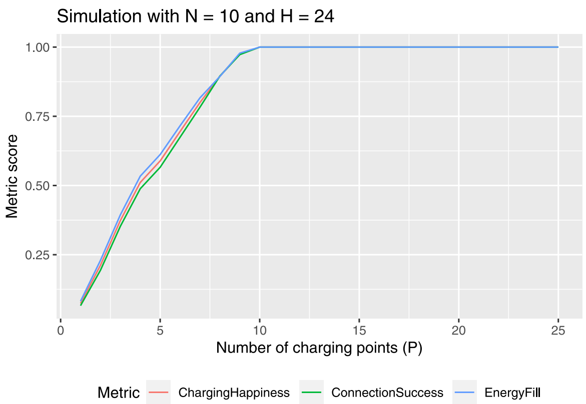

Fig. 7. Simulation for $N = 10$ and $H = 24$.

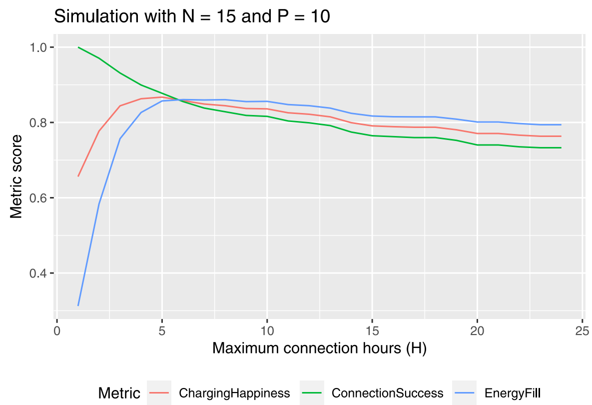

Fig. 9. Simulation for $N = 15$ and $P = 10$.

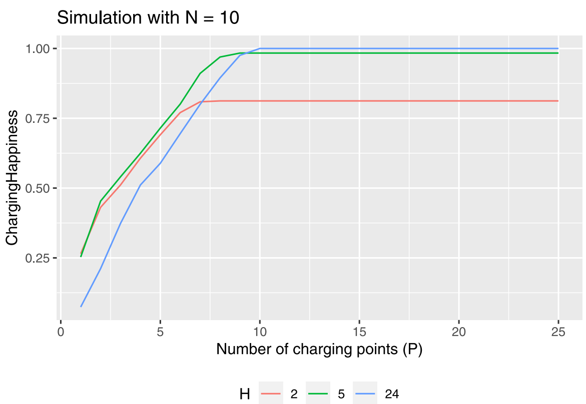

Fig. 8. Simulation for $N = 10$.

$ConnectionSuccess$ scores but with a high penalty on the $EnergyFill$ metric, which decreases the global $ChargingHappiness$ metric.

Therefore, a balanced value of P and H will be required, and it will depend on the type of EV demand in the specific study case. For example, if a charging hub is located in a factory parking where all workers must enter at the same time, the only solution to increase $ChargingHappiness$ would be to expand the number of charging stations since the crucial metric will be the $ConnectionSuccess$. Limiting the connection time would have no positive effect on the global $ChargingHappiness$. On the other hand, if the factory has two different work shifts, the introduction of a connection limit would make sense in order to let the latter users connect the vehicle. Therefore, the EV user profile modelling approach proposed in this work is essential to simulate this kind of regulatory measures for charging hubs.

4.2. Assessment of a real charging hub

This section raises two different approaches for the assessment of charging hubs that foresee a growing scenario of daily EV demand. The current number of charging points in the pilot is $P = 8$. Currently, the infrastructure is not undersized, but they are interested to know when the $ChargingHappiness$ will decrease and what measures they could take to increase it again. When there are no limitations in the connection time ($H = \infty$) and $P = 8$, which is the current case, the $ChargingHappiness$ decreases according to the number of sessions per day N, as shown in Fig. 10.

The $ChargingHappiness$ decreases drastically from $N = 9$, and it is also visible that both sub-metrics, $ConnectionSuccess$ and $EnergyFill$, have similar behaviours. Hereupon, two different approaches are assessed to increase the users' $ChargingHappiness$: (1) introduce a maximum connection time and (2) increase the number of charging points. The $ChargingHappiness$ of both approaches is compared to the black line shown in Fig. 10 as a baseline.

4.2.1. Optimal H given N and P

In this scenario, the charging hub operator is not planning to extend the infrastructure (i.e. install more charging points) but is concerned about the increase of failed sessions (i.e. vehicles that cannot connect because of full occupancy) in the near future. Thus, they have decided to limit the connection time of charging sessions but they want to know what is the optimal limit for their case study.

From the metrics table the values corresponding to $P = 8$ have been extracted and, from these values, the H that gives the maximum

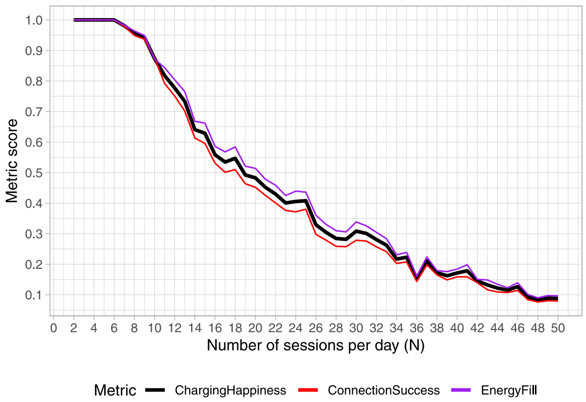

Fig. 10. Baseline with $P = 8$ and no regulation ($H = \infty$).

$ChargingHappiness$ for every value of N has been selected. The results obtained are shown in Fig. 11, which describes the maximum $ChargingHappiness$ obtained when limiting the connection (coloured columns) or without limitation (black line). The colour of the columns corresponds to the optimal H, i.e the highest H values that give the maximum $ChargingHappiness$. It is visible that when there is a small number of daily sessions the optimal limitation is a high value, near to not limiting the sessions, since the priority is to charge all vehicles completely. However, when $N > P$, the optimal limitation tends to small values, concretely between 4 and 5 h, since the priority is to charge all vehicles as fully as possible to keep an acceptable average $ChargingHappiness$. Besides, for small values of H, for example, columns corresponding to $H = 3$, more different vehicles can connect, so $ConnectionSuccess$ increases, but $EnergyFill$ decreases since there is not enough time to charge the vehicle.

Finally, Fig. 11 also shows the benefits of limiting the connection time when the charging infrastructure is undersized, comparing the $ChargingHappiness$ obtained with the baseline black line (i.e. no limitation). Therefore, a proper solution for this case study would be to regulate the connection time up to 5 h, with the possibility of decreasing the limit to 4 h if the charging hub receives more than 16 sessions per day.

4.2.2. Optimal P given N, H and minimum level of ChargingHappiness

A different scenario could be that the charging hub operator decides not to limit the connection time ($H = \infty$) because it is possible to extend the charging hub (i.e. increase the number of charging points P). However, since every new charging station requires a high investment, the charging hub investor wants to know the optimal number of charging points that would give a minimum $ChargingHappiness$ of 75%, for example. In this scenario, the optimal P of every N value is the lowest P that gives the minimum $ChargingHappiness$. The metrics values from the metrics table corresponding to $P > 8$ and $H = \infty$ are illustrated in Fig. 12, showing the optimal number of charging points that gives the desired minimum of $ChargingHappiness$ for every value of N, compared with the baseline ($P = 8$). With the original charging infrastructure, $P = 8$, a $ChargingHappiness$ of 0.75 is achieved until 12 sessions per day. From $N = 38$ a happiness level of 0.75 cannot be achieved with the maximum of 25 charging points that this simulation has considered.

The relationship N/P is not completely direct since a value of 13 or 14 charging points, for example, would be optimal in a range of N from 19 to 22 sessions per day. Note that when sizing the number of charging points, the distribution of the sessions over the day is very important, since a value of $N = 10$ could be 10 sessions starting at 9:00 AM or spread throughout the day. In that sense, modelling and simulating the charging sessions by user profile is crucial to obtain proper results for a specific study case.

5. Conclusions and further research

This work provides a methodology to assess charging hubs in terms of size (i.e. the number of charging points P) and regulation (i.e. limitation of connection time H), considering the interests of both charging hub operators and EV users through the $ChargingHappiness$ metric.

A real data set of charging sessions has been used to validate the modelling and simulation methods proposed. This novel framework to model EV user profiles allows the estimation of EV demand in future scenarios but also in places with absent charging infrastructure or without available data. The user-profile approach offers the possibility to define the percentage of sessions from every profile in a tailored way, adapting the models to multiple use cases. However, the fact that the models are built from real data sets could be also a limitation for places where the charging load has very specific behaviours. Taking the example at issue, the EV user profiles from a Norwegian Harbour could not be suitable to simulate the EV demand in a supermarket's charging hub but could be useful for other industrial areas.

In this work, the models have been used to simulate higher EV demand in the existing charging hub in Borg's Harbour. The analysis of the results from these simulations provided the following conclusions:

- When a charging hub is undersized and not regulated, the $ChargingHappiness$ decreases because not all the vehicles are able to connect.
- When introducing a limit on the connection time, it is important to consider the average charging time since low values of H could prevent the vehicles from charging all their energy requirements. Generally, this could entail low $ChargingHappiness$ even though more vehicles are able to connect.
- The average charging time and the EV user profiles are not the same for every use case (e.g. charging power, average distance, work schedules, etc.), so the EV data set used to build the stochastic models will be a determining factor.
- The optimal growth of charging points in a charging hub is not directly proportional to the growth of EV demand, since it is determined by the type of user profiles and the corresponding distribution of vehicles over the day.
- Modelling EV sessions based on user profiles is essential to accurately analyse the occupancy of charging hubs and the corresponding saturation scenarios.

Finally, the authors want to describe some points for further research on this topic. The occupancy algorithm presented assumes that users perfectly respect the connection limit. This is valid as a best-case analysis but a realistic implementation should consider a small percentage of users that do not disconnect the vehicle right after the end of the connection limit. Moreover, users may not be satisfied if forced to disconnect the vehicle, so this factor could also be considered in the $ChargingHappiness$ metric definition. Furthermore, this regulation measure could be applied in a more dynamic way, for example, by defining the optimal time limit according to the proportion of each user profile and the day of the week.

CRediT authorship contribution statement

Marc Cañigueral: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Llorenç Burgas:** Conceptualization, Investigation, Methodology, Validation, Writing – original draft. **Joaquim Massana:** Conceptualization, Investigation, Methodology, Validation, Writing – original draft. **Joaquim Meléndez:** Supervision, Writing – review & editing. **Joan Colomer:** Supervision, Writing – review & editing.

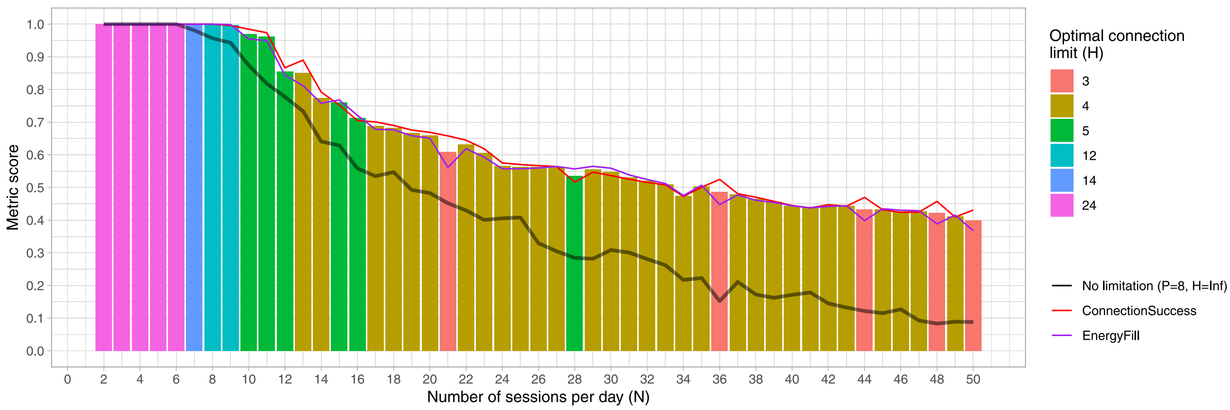

Fig. 11. *ChargingHappiness* for a charging infrastructure with $P = 8$.

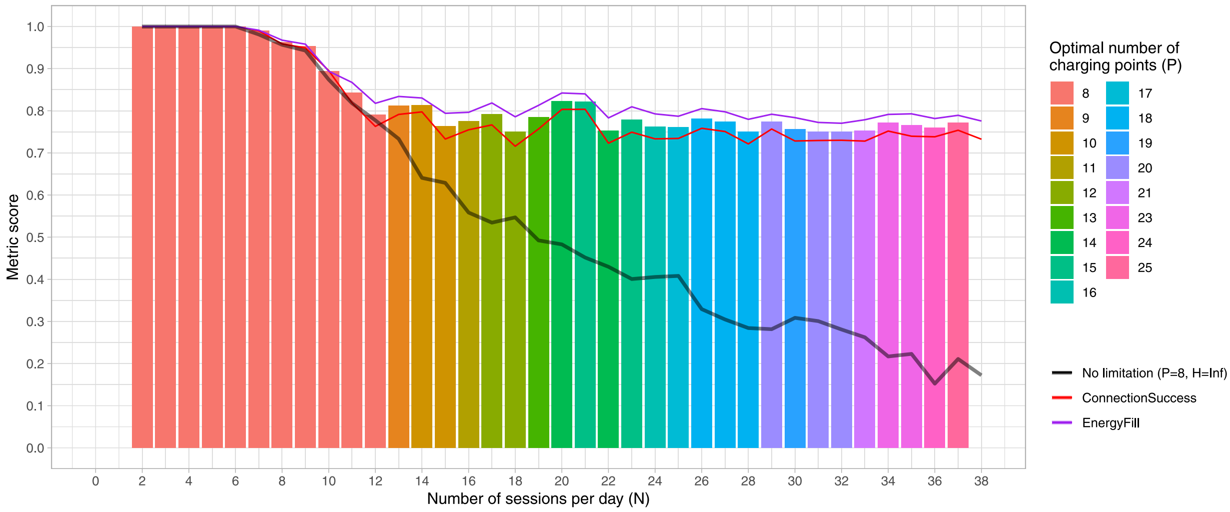

Fig. 12. *ChargingHappiness* for a charging infrastructure without connection limit.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Chapter 5

Enabling high penetration of electric vehicles using smart charging based on local and dynamic capacity limits

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Enabling high penetration of electric vehicles 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 (EV) public charging infrastructure to reach the carbon-neutral objectives, the Distribution System Operator (DSO) can not 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 EV penetration, considering dynamic and local power limits, in order to assess the impact on both the satisfaction of EV users and the business model of the Charging Point Operator (CPO). A stochastic approach, based on Gaussian Mixture Models (GMM), has been used to model different profiles of EV users using data from the Amsterdam public EV charging infrastructure. Several key performance indicators have been defined to assess the impact of such charging limitations on the different stakeholders. Results show that, while Amsterdam's existing public charging infrastructure can host just twice the current EV 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 EV users. These results foresee Flexpower as an essential mechanism for the Municipality of Amsterdam to accelerate the electric mobility transition while providing a reliable peak-shaving strategy with a minimal impact on the charging market.

Keywords: electric vehicles, smart charging, user profiles, Gaussian Mixture Models, charging infrastructure

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 quality supply, and the municipalities or regulators, who want to expand the charging infrastructure.

A major bottleneck is because the power demand from electric vehicles mainly coincides with the demand from households alongside other sources of electrification (i.e. heating, cooking, etc.) [2, 3, 4, 5, 6]. This results in daily demand peaks that can reach the maximum capacity of some low-voltage transformers. 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 can 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

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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 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, 12, 13]. However, a city-scale smart charging deployment is still a challenge due to a combination of technical, economic and societal issues. 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 Charge Point Operator (CPO), the mobility/charging necessities of EV users and the charging infrastructure deployment plans of cities and/or governments [14]. It is also important to remark that most of the literature does not take into account the local grid constraints but global approaches considering implicit flexibility strategies based on the electricity price [15, 16, 17], the impact of renewable production at transmission-level [17, 18, 19, 20], national flexibility markets [12] or modelling user profiles at wide-scale[11, 21, 22]. However, the real impact of distributed renewable energy sources (RES) and electromobility is in the low-voltage grid and this impact is diverse depending on the location and time. Thus, despite the low degree of instrumentation of these infrastructures, LV lines and transformers are the first assets to protect from the volatility of local RES generation and overloads produced by EVs. 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 concerns and offer more information to all stakeholders of the Flexpower project. The study uses real data from a trial at 124 public charging points to model EV user profiles and uses these models to generalise the study across different locations and time periods in order to generalise the conclusions. To achieve that, multiple scenarios simulating real charging sessions and the implementation of Flexpower in Amsterdam have been developed and properly described in Section 3. Section 4 explains the calculations and simulations performed to later analyse the results in Section 5. 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 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 3x25 amperes, which means that, traditionally, every charging station had a technical capacity of 25A. 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 3x35A 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 x 8A 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 3x16A 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 signal. This signal is computed by the DSO considering the nominal power of every low-voltage transformer (MSR, middenspanningsstation in Dutch [31]) and the forecasted demand. Thus, on 62 public charging stations (124 charging points) that constitute the pilot, a daily profile for the maximum charging capacity, at the resolution of 15 minutes, is planned by the DSO. The Flexpower3 strategy also assures a minimum charging capacity agreed upon together with the CPO. An example of this maximum capacity plan for a specific MSR participating in Flexpower3 during September 2022 is shown in Figure 1. Thus, the CPO has to limit the maximum charging power of the stations installed in the feeder dynamically at this 15-minute resolution in order to not overpass the allocated capacity of the transformer for charging EVs. Consequently, if the EV demand in the MSR is higher than the capacity limit, the CPO must distribute the maximum allocated capacity among all the charging stations located downstream. The available capacity is equally divided across all charging stations, always respecting a minimum of 8A per vehicle since some EV models stop charging below low current levels. If the available capacity per charging station is lower than 8A, a queuing system is activated in which charging sessions are rotated every 15 minutes.

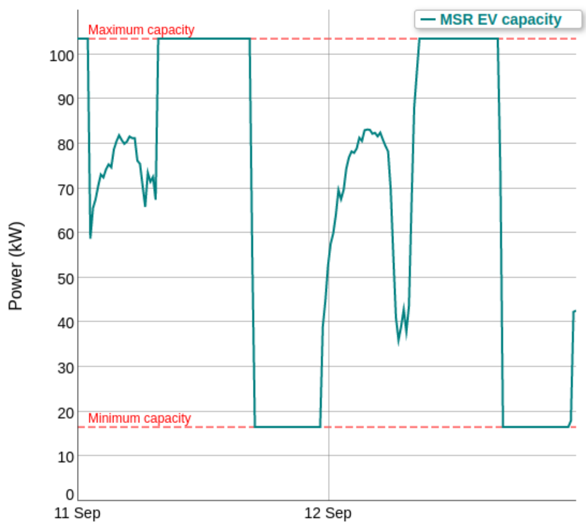

Figure 1: MSR (low-voltage transformer) capacity sent by the DSO

Figure 1 also shows constant minimum and maximum limits in a red dashed line. These maximum and minimum capacity limits are obtained according to Equations 1 and 2 respectively, and are given by the number of charging stations installed downstream the MSR and the values of *ReservedCapacity* and $FirmCapacity$:

- *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 by Flexpower program.

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

Observe that the capacity limit in Figure 1 is represented in power units to facilitate the understanding of the power system, despite the DSO defining it in amperes per phase because it is a three-phase distribution system. Thus, the limits obtained with Equations 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 Figure 1), are converted to power capacity considering a three-phase low-voltage system. 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 to supply 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.

Section 4 is devoted to simulate different scenarios to find the optimal $FirmCapacity$ that ensures a good service to users but also a reliable demand profile for the distribution grid.

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.

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.

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 (1x16A, 2x16A or 3x16A), 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 minutes.

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 [32]. 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 16A). 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 3.7kW and 80% at 7.4kW), 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 [33].

Therefore, stochastic models are built from the real Amsterdam data set described in Section 3.1.1 to characterise 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 [34].

3.2.1. *Clustering EV charging sessions into user profiles*

In the first step, a Gaussian Mixture Models clustering is applied to the data set of EV charging sessions. Gaussian Mixture Models (GMM) is a model-based clustering technique that groups data points into Gaussian distributions. The clustering methodology is widely explained in previous works, first in [35] and later improved in [36]. In this application, two variables are used to cluster sessions using a bivariate GMM: connection start hour and duration (connection hours).

As raised in [36], model-based algorithms are sensitive to outliers so first, the full data set is divided into smaller sets with similar density levels and the outlying sessions are cleaned using the DBSCAN clustering method. This data division also takes into account the different time cycles where the EV users have different behaviour (day of the week, season, etc.). Second, 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. Then, 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 hours 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.

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 connection model of a specific user profile is built as an additive combination of the multiple bivariate Gaussian distributions (i.e. clusters) associated with that user profile.

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 [37] 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 16A), 7.4 kW (i.e. two-phase connection at 16A) and 11kW (i.e. three-phase connection at 16A) [3]. Therefore, the full data set of sessions has been first split by user profile and second by charging rates to obtain the different Energy Gaussian Mixture Models. This improvement in the methodology respective to the initial method raised in [37] has been also introduced in the latest version of the open-source R package `evprof` [34].

Even though the charging power is now considered while building the energy models, the power variable itself is not modelled since it is estimated according to the environment of the case study, like the characteristics of the charging infrastructure or the EV models in the current EV fleet, as 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. 3.7kW, 7.4kW, 11kW, 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 (3.7kW, 7.4kW and 11kW). 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" [38] 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, an algorithm has been developed 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.

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 minutes 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 16A, while the grid connection has a maximum of 25A. Then, a vehicle can charge at 16A when it is alone in the charging station, but the maximum current will be reduced to 12A 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 16A 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. This algorithm sets for every charging session the maximum charging power and the corresponding energy consumed in every 15 min time slot of the simulation time sequence. With this purpose, the simulated schedule of charging sessions is expanded among all time slots. In order to better visualize the process, Appendix A includes Table A.1, which shows an example of a normal schedule (named S), and Table A.2, which shows an example of the schedule expanded in time (named SE). The nomenclature of variables used in Algorithm 1 is described in Table 2.

The *Power* and *Energy* variables of the expanded schedule SE are initialised 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 found 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 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 Figure 2, 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.1 - B.7 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, Figure 3 validates that the charging power has also a clear impact on the amount of energy charged by the vehicle,

```
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 ≤ 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 × 230 × Phases_s)/1000     // Update Power in SE
        PotentialEnergy = Power_s,t × ΔT
        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

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.8-B.54 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 Figure 4). The share of every user profile in every MSR is shown in Figure 5, 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 dif-

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 hours (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

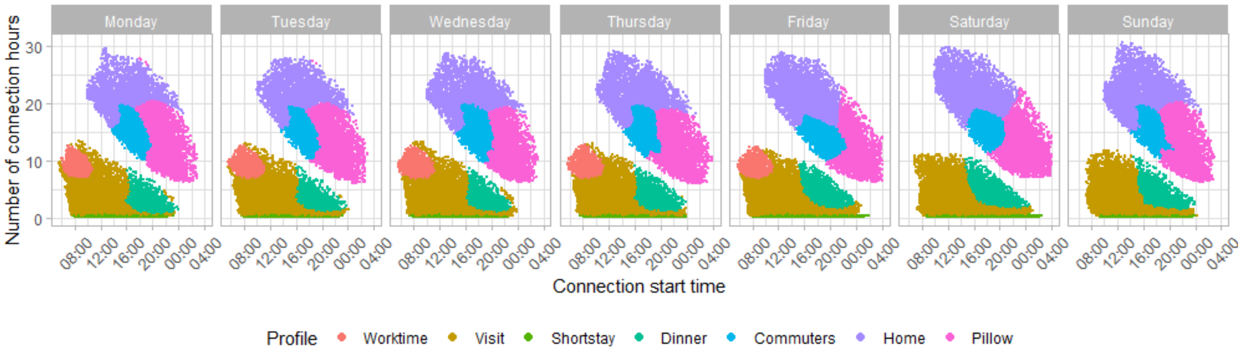

Figure 2: Real data set of EV charging sessions classified into generic User profiles

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

ferences 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 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 can not 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, Figure 6 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 of charging sessions has to be linked to the growth of the infrastructure.

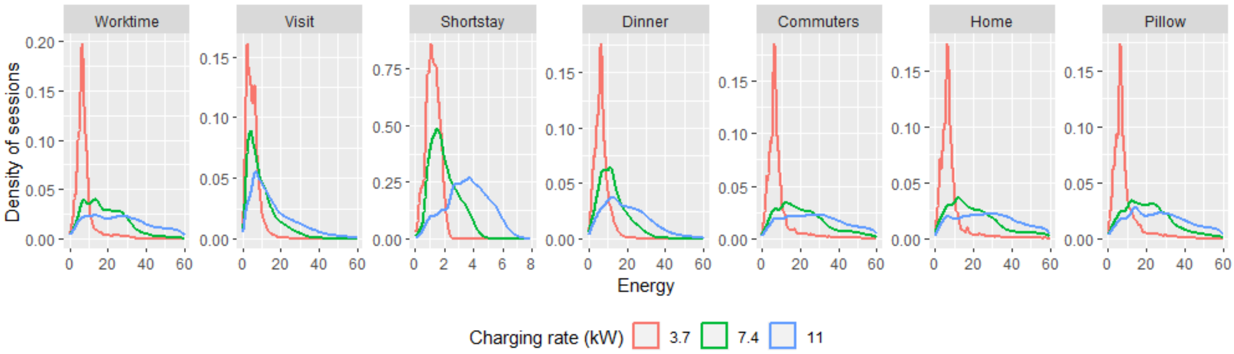

Figure 3: Density curves for energy values of sessions belonging to every user profile and charging rate

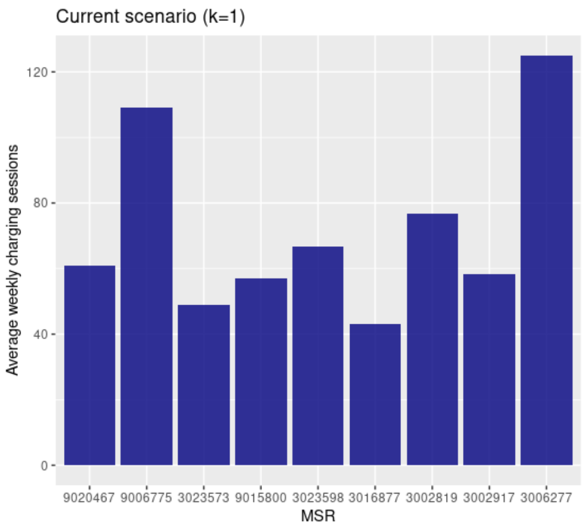

Figure 4: Current weekly sessions for every MSR of the study

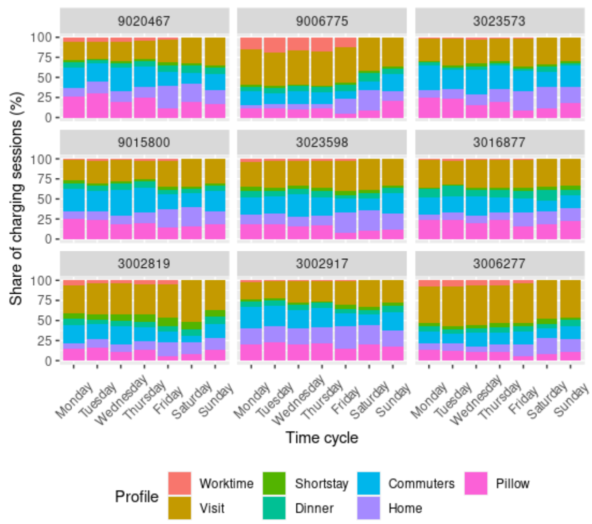

Figure 5: Share of user profiles for every MSR of the study

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. Figure 7 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 1A in the current scenario ($k = 1$) would suppose 25% of uncompleted sessions whereas a Firm capacity of 4A, reduces it until a 5%, and the 25% with this Firm Capacity is reached when $k = 7$. Increasing Firm capacity to 6A results in a percentage of uncompleted sessions around 10% for all the EV penetration scenarios.

5.2. DSO perspective

Figure 8 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

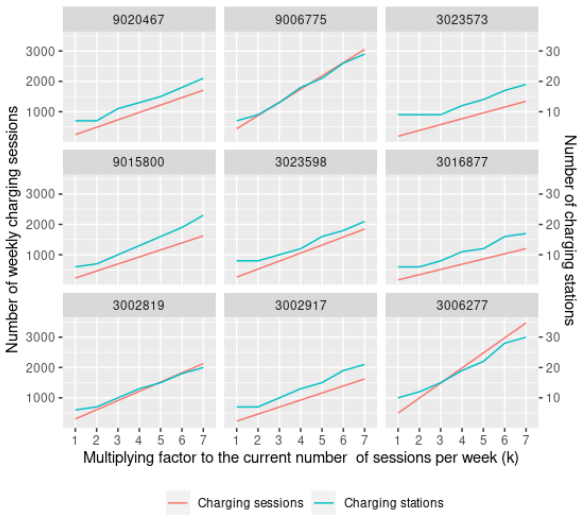

Figure 6: Infrastructure growth according to sessions/week

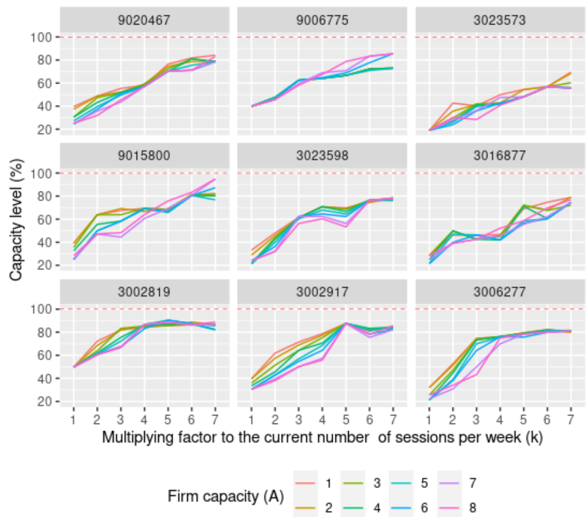

Figure 8: MSR capacity reached according to sessions/week

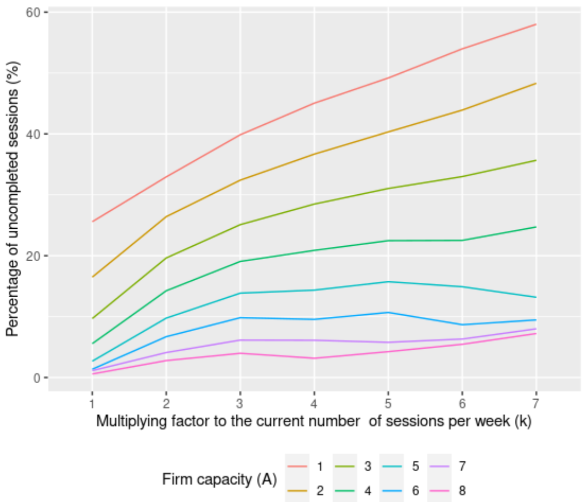

Figure 7: Uncompleted sessions according to sessions/week

40% and 50% of the capacity respectively.

For MSR 9006775, the peak demand is the same for all *Firmcapacity* values from 1 to 5A. 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 Figure 9, for firm capacity values of 1A (left) and 4A (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 Figure 9, 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 Figure 8, 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.

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 Figure 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. Figure 10 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

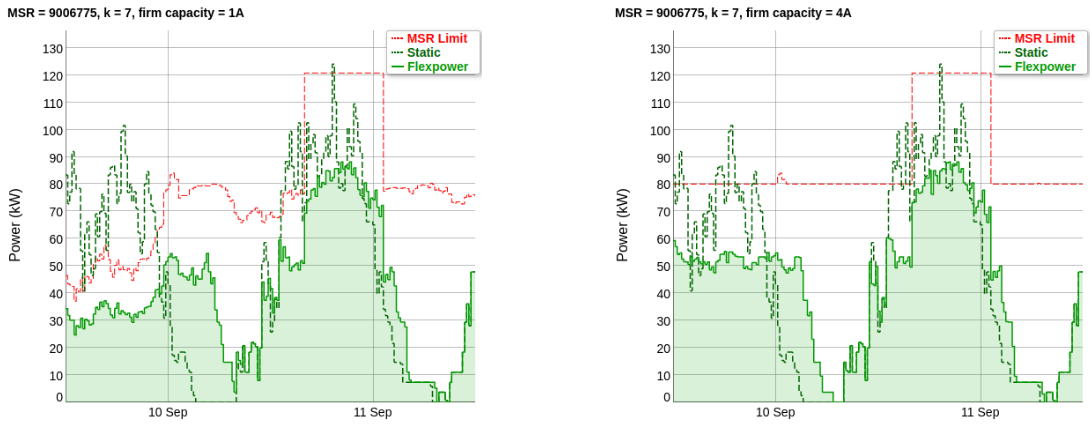

Figure 9: MSR 9006775 with k = 7, comparing $FirmCapacity$ = 1 (left) and $FirmCapacity$ = 4 (right)

reduction is relative to the demand itself. For most MSRs, the peak reduction with a firm capacity of 1A remains between 80% and 90%, with 4A between 70% and 80%, with 6A around 60% and with 8A 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 Figure 11, 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 Figure 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. Figure 12 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 4A 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

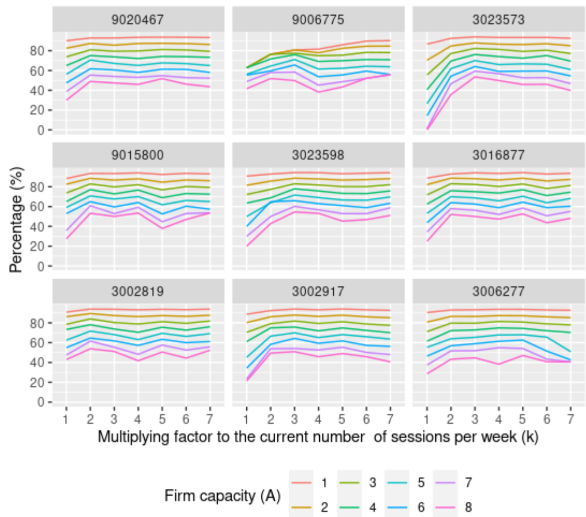

Figure 10: MSR peak reduction according to sessions/week

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 Figures C.2 and C.3 from Appendix C respectively. Figure C.2 shows how the EV demand in MSR 3002917 is lower than the maximum capacity, while Figure 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 Figure 9).

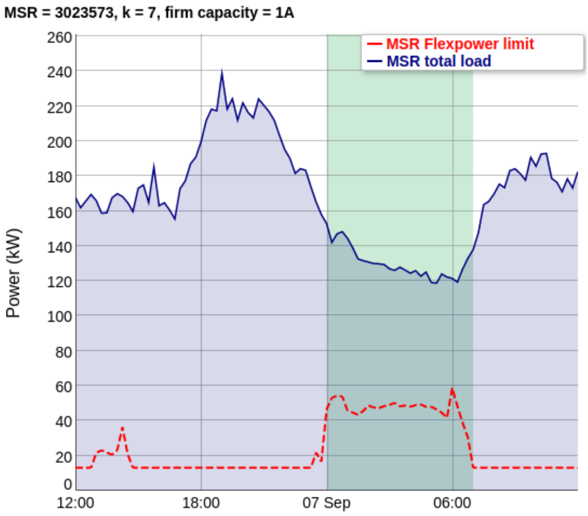

Figure 11: MSR limit according to total power demand

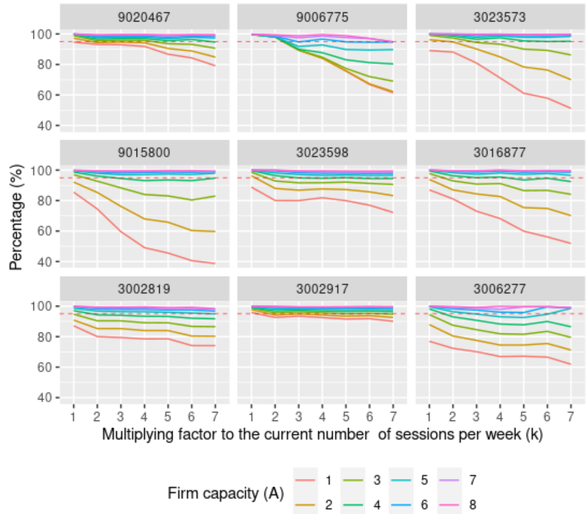

Figure 12: Share of total energy charged according to sessions/week

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, Figure 13 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 5A 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, Figure 14 shows the average percentage of energy charged for every charging rate and k scenario, considering a Firm capacity of 4A (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 Figure 14 decrease due to outlying sessions with really high energy demand.

Finally, it is also interesting to see the impact by user profile, represented in Figure 15. 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 4A 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.

- Uncompleted sessions, in percentage, representing the Municipality's objective to ensure a high-quality charging service to Amsterdam EV users.

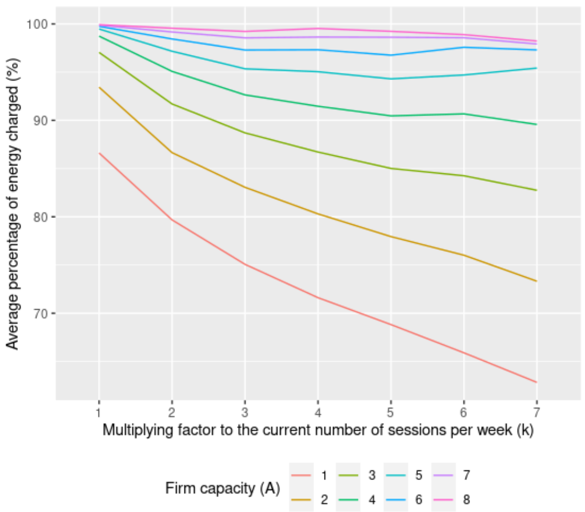

Figure 13: Average percentage of energy charged according to sessions/week

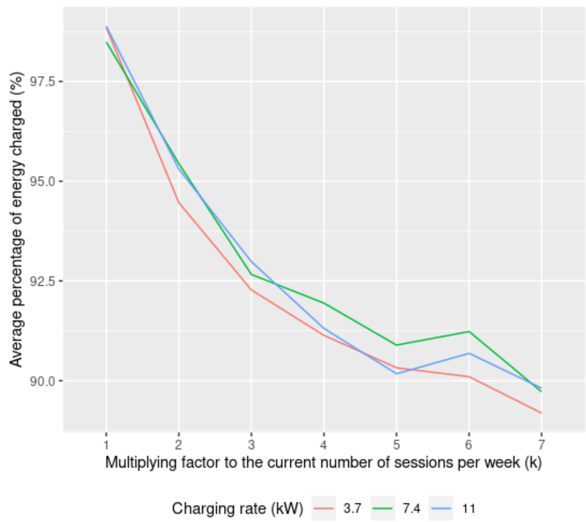

Figure 14: Average percentage of energy charged according to charging power and sessions/week, considering a Firm capacity of 4A

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%.

These indicators are calculated for every scenario of firm capacity and EV penetration (k) and represented in coloured tables. Figure 16 shows the indicators for the current EV penetration ($k = 1$), while the future scenarios with higher EV penetration are represented in Tables 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, Figure 16 (i.e. current scenario) shows that a Firm capacity of 1A only provides an acceptable scenario for the DSO, and that the optimal value of Firm capacity would be 4A (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. Figures D.1 - D.6, the recommended firm capacity value to ensure an equilibrated scenario for all stakeholders would go up to 6A, 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 summarises the main conclusions obtained in this work, as well as some recommendations that arise from previous sections.

Thanks to the implementation of the smart charging project Flexpower, more charging stations will be able to be installed under the same grid and MSRs that supply the current charging infrastructure. Currently, every MSR has a specific power capacity reserved for EV demand, depending on the current number of charging stations installed downstream. In Flexpower, this reserved capacity is not constant but variable according to the total power demand in the MSR. Therefore, the charging

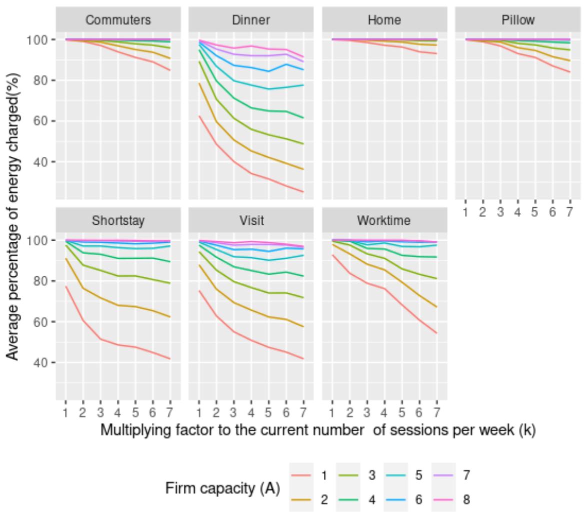

Figure 15: Percentage of uncompleted sessions for every user profile according to the number of weekly sessions

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

Figure 16: Summary of results from current EV penetration (k = 1)

power of sessions is limited by the CPO according to the MSR's maximum capacity signals sent by the DSO with 15 minutes resolution. A full month of EV sessions has been simulated for different EV penetration scenarios, considering the real MSR capacity limits from September 2022. The main conclusions obtained from simulating Flexpower in every scenario can be summarised in the following points:

- The majority of MSRs analysed in this study are able to host double the current number of EV sessions without the need of installing more charging stations.
- If the communication CPO-DSO works and Flexpower is implemented without interruptions, the EV demand will not surpass the MSR's capacity and there will not be congestion in the power grid even though the charging infrastructure keeps growing.
- In the MSRs where the Flexpower project works properly, the charging infrastructure could be extended in order to provide a good charging service to EV users in Amsterdam that request a public charging station in their street.
- The actual firm capacity value of 4A is optimal for the current EV demand and provides an equilibrated solution for all stakeholders, allowing a peak demand reduction of approximately 70% with only 6% of uncompleted sessions and a minimal user impact.
- For the future EV penetration scenarios, the recommended general firm capacity value would be 6A, even though it could vary according to the MSR congestion level. In average, a firm capacity of 6A would provide a percentage of uncompleted sessions of around 10%, a demand peak reduction of around 60%, the total energy sold higher than 98% and the average energy charged by users higher than 97%.
- Flexpower could suppose a highly reliable peak-shaving method for the DSO in order to avoid grid congestion during peak hours.
- The aggregated peak demand could even be higher with Flexpower due to the rebound effect after peak hours. However, the rebound period coincides with the valley hours of the rest of the power demand, since the DSO defines the MSR limits based on forecasts. Therefore, the demand forecast must be done properly in order to minimize the risk of a rebound effect during peak-demand hours.
- In the MSRs with Flexpower capacity limits below the actual maximum capacity, presumably because the rest of demand (buildings, data centres, etc.) represents a large share, the limitation of the energy charged to EVs increases dramatically for firm capacities lower than 4A.
- There are no relevant differences between different charging rates (3.7 kW, 7.4 kW or 11kW) in terms of individual EV impact, since the higher the charging power the higher the energy demand.
- In districts with a predominance of short-connection user profiles (i.e. Visitors, Shortstay, Dinner) the implementation of Flexpower will have a higher impact on their charge. Further work

could consider a Flexpower simulation with a priority of power limitation according to the User profile assigned to the connected vehicles.

Besides the simulation of Flexpower, during the EV modelling process developed in Section 4.1, this work found out that the energy charged by an EV session highly depends on the charging power. This is explained by the fact that the new EV models that can charge at higher charging rates also have larger batteries. Therefore, the future EV demand is going to grow not only according to the size of the EV fleet but also because of the batteries' size. However, the charging frequency could also be reduced because of the larger batteries, so e.g. instead of charging twice a week, people could tend to charge only once. This could be validated with a data set of EV charging sessions counting with a vehicle's unique ID variable, in order to track the charging frequency of the vehicles and analyse the possible differences between the different EV models. This variable was not in the data set used in this work, so it would be of high interest for further research works.

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. However, the capacity limits may increase together with the EV demand so further work should consider a redefinition of these limits for the simulations, or an algorithm to generate the MSR limits according to the total power demand. In both cases, more data from the DSO would be required.

Author contributions

Marc Cañigueral is the main author of the paper, who developed the tools and contributed to the analysis of data sets. Rick Wolbertus contributed to the concept of this research and completed the manuscript. Joaquim Meléndez contributed to specific aspects of the modelling process, supervision of the research and revision of the text.

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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.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

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

This appendix exposes the statistical features (location and variance) of the bivariate GMM for the connection variables (i.e. connection start time and connection duration) and the univariate GMM for the energy variable. 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.

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

Table B.1: Connection GMM - Time cycle: Monday

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

Table B.2: Connection GMM - Time cycle: Tuesday

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

Table B.3: Connection GMM - Time cycle: Wednesday

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

Table B.4: Connection GMM - Time cycle: Thursday

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

Table B.5: Connection GMM - Time cycle: Friday

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

Table B.6: Connection GMM - Time cycle: Saturday

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

Table B.7: Connection GMM - Time cycle: Sunday

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.9: Energy GMM - Time cycle: Monday, User profile: Visit

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.8: Energy GMM - Time cycle: Monday, User profile: Worktime

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.10: Energy GMM - Time cycle: Monday, User profile: Shortstay

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.11: Energy GMM - Time cycle: Monday, User profile: Dinner

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.12: Energy GMM - Time cycle: Monday, User profile: Commuters

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.13: Energy GMM - Time cycle: Monday, User profile: Home

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.14: Energy GMM - Time cycle: Monday, User profile: Pillow

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.15: Energy GMM - Time cycle: Tuesday, User profile: Worktime

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.16: Energy GMM - Time cycle: Tuesday, User profile: Visit

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.17: Energy GMM - Time cycle: Tuesday, User profile: Shortstay

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.18: Energy GMM - Time cycle: Tuesday, User profile: Dinner

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.19: Energy GMM - Time cycle: Tuesday, User profile: Commuters

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.20: Energy GMM - Time cycle: Tuesday, User profile: Home

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.21: Energy GMM - Time cycle: Tuesday, User profile: Pillow

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.22: Energy GMM - Time cycle: Wednesday, User profile: Worktime

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.23: Energy GMM - Time cycle: Wednesday, User profile: Visit

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.24: Energy GMM - Time cycle: Wednesday, User profile: Shortstay

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.25: Energy GMM - Time cycle: Wednesday, User profile: Dinner

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.26: Energy GMM - Time cycle: Wednesday, User profile: Commuters

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.27: Energy GMM - Time cycle: Wednesday, User profile: Home

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.28: Energy GMM - Time cycle: Wednesday, User profile: Pillow

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.29: Energy GMM - Time cycle: Thursday, User profile: Worktime

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.30: Energy GMM - Time cycle: Thursday, User profile: Visit

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.31: Energy GMM - Time cycle: Thursday, User profile: Shortstay

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.32: Energy GMM - Time cycle: Thursday, User profile: Dinner

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.33: Energy GMM - Time cycle: Thursday, User profile: Commuters

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.34: Energy GMM - Time cycle: Thursday, User profile: Home

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.35: Energy GMM - Time cycle: Thursday, User profile: Pillow

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.36: Energy GMM - Time cycle: Friday, User profile: Worktime

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.37: Energy GMM - Time cycle: Friday, User profile: Visit

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.38: Energy GMM - Time cycle: Friday, User profile: Shortstay

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.39: Energy GMM - Time cycle: Friday, User profile: Dinner

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
	3.70862	0.117659	20
	3.985759	0.088152	12
	4.149102	0.031346	2

Table B.40: Energy GMM - Time cycle: Friday, User profile: Commuters

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.41: Energy GMM - Time cycle: Friday, User profile: Home

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.42: Energy GMM - Time cycle: Friday, User profile: Pillow

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
	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.43: Energy GMM - Time cycle: Saturday, User profile: Visit

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.44: Energy GMM - Time cycle: Saturday, User profile: Shortstay

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.45: Energy GMM - Time cycle: Saturday, User profile: Dinner

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
	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.46: Energy GMM - Time cycle: Saturday, User profile: Commuters

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.47: Energy GMM - Time cycle: Saturday, User profile: Home

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.48: Energy GMM - Time cycle: Saturday, User profile: Pillow

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
	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.49: Energy GMM - Time cycle: Sunday, User profile: Visit

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.50: Energy GMM - Time cycle: Sunday, User profile: Shortstay

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.51: Energy GMM - Time cycle: Sunday, User profile: Dinner

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

Table B.52: Energy GMM - Time cycle: Sunday, User profile: Commuters

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.53: Energy GMM - Time cycle: Sunday, User profile: Home

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

Table B.54: Energy GMM - Time cycle: Sunday, User profile: Pillow

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.

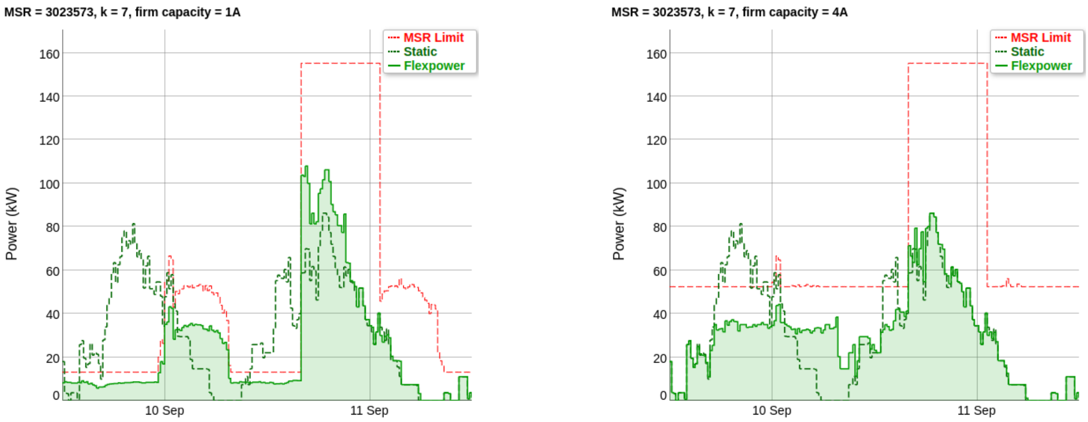

Figure C.1: MSR 3023573 with k = 7, comparing $FirmCapacity$ = 1 (left) and $FirmCapacity$ = 4 (right)

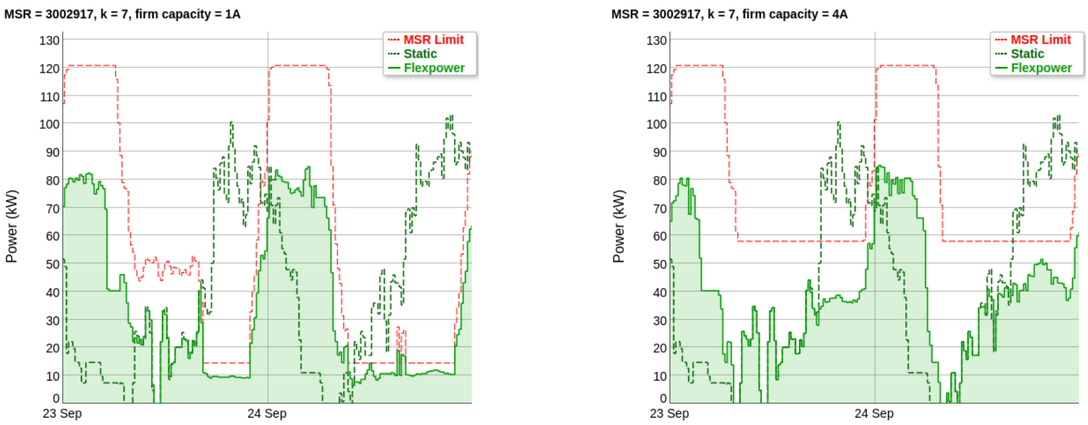

Figure C.2: MSR 3002917 with k = 7, comparing $FirmCapacity$ = 1 (left) and $FirmCapacity$ = 4 (right)

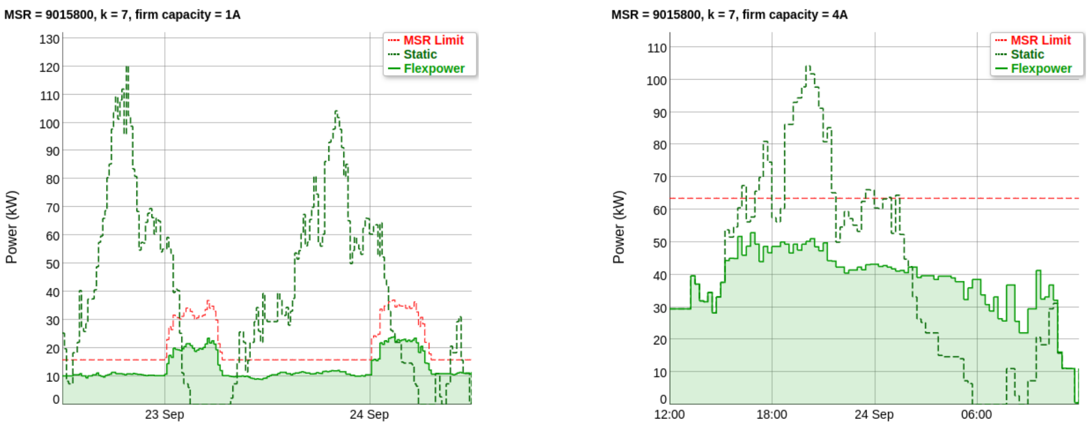

Figure C.3: MSR 9015800 with k = 7, comparing $FirmCapacity$ = 1 (left) and $FirmCapacity$ = 4 (right)

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

Figure D.1: Summary of results from EV penetration scenario $k = 2$

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

Figure D.2: Summary of results from EV penetration scenario $k = 3$

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

Figure D.3: Summary of results from EV penetration scenario $k = 4$

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

Figure D.4: Summary of results from EV penetration scenario $k = 5$

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

Figure D.5: Summary of results from EV penetration scenario $k = 6$

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

Figure D.6: Summary of results from EV penetration scenario $k = 7$

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Chapter 6

Main results and discussion

This thesis contributes to addressing critical aspects of the transition to EVs by introducing methodologies for clustering and modelling EV user profiles, proposing flexibility management strategies, and providing insights into charging infrastructure planning. An unplanned and massive penetration of EVs impacts on the capacity of the power grid due to their high charging power and concentration of this demand in space (location of charging stations) and time (repetitive and coincident charging habits), resulting in demand peaks that can cause congestions in the existing power infrastructure at the low-voltage level. A complete methodology to characterise EV users (profiling and modelling) enabling stochastic simulation allows identifying the potential of aggregated flexibility embedded in these profiles. The use of these EV user models to improve operation, management and planning of charging strategies is completely new in the field. This approach introduces several benefits and guidance to the stakeholders involved in the electric mobility ecosystem. Among them: the DSO to defer investments on infrastructure to increase the capacity, better service offered by CPOs and the consequent satisfaction of EV users; or new tools to improve planning of charging infrastructures at district/city level. The following sub-sections present the key findings in each area of research, derived from the results of the three journal articles in this compendium.

6.1 Clustering EV user profiles

This thesis covers the application of clustering and modelling techniques to discover underlying trends and similarities among EV users, thereby providing valuable insights into user behaviour, connection patterns and the corresponding flexibility potential.

Among the different clustering techniques used in literature, the clustering method selected for this application is the Gaussian Mixture Models (GMM), a model-based clustering method that makes use of Expectation-Maximization (EM) algorithm to define the clusters. The main reason to select a model-based clustering technique in the EV users field is to take into account the stochasticity of the data and the randomness in humans' daily behaviour.

However, the application of the methodology with the different data sets used in this thesis made clear that GMM clustering is highly dependent on the dispersion of the data points. For this reason, two different pre-processing steps have successfully improved the clustering results and the determination of model-based clusters. On one hand, a logarithmic transformation is essential to avoid underperforming the clustering method due to the crisp distribution of time data (inexistence of negative values). This transformation is also used to reduce sparsity between data points and better define the shape of the density curves. On the other hand, cleaning outliers also improves the performance of GMM clustering, as introduced in a conference paper by the author [19]. Using a density-based clustering algorithm such as DBSCAN resulted in a very practical way to identify the data points outside the most relevant density distributions (i.e. outliers). Combining two different clustering techniques is not a common approach in the existing bibliography but, in the case of clustering EV charging sessions, this methodology worked as expected in all data sets in which it has been validated.

As introduced in Chapter 1.3.1, the GMM clustering requires to pre-define the number of clusters and the BIC approach has been used for this parameterization. In all cases, the convergence in the fitting process came from VVV models (i.e. ellipsoidal, varying volume, varying shape and varying orientation). It is logical since all clusters can be different in volume, shape and orientation, and the ellipsoidal shape reflects that always there is one variable (i.e. connection start or connection duration) that has a higher variability than the other one.

After obtaining the clusters, it is appropriate to add a second-step classification or profiling step in order to face the modelling methodology from a more abstract level. Each cluster has been labelled with a generic user profile name according to their respective interpretations. These interpretations have not only been based on the centroid's values of connection start time and duration, but as well on the shape of the corresponding ellipses, which represent the covariance matrix of each cluster. A wider ellipse means a less concrete definition of the user profile.

From the three data sets analysed in this thesis, the user profiles found in Arnhem and Amsterdam show big similarities, while more different patterns were found in the Norwegian harbour in Borg. Since the city data sets show representative user profiles, it is interesting to briefly describe these common patterns in the use of public charging infrastructure:

- Commuters: Sessions at home directly after work, leaving always the following morning. Only present in the Workday time cycle. Low variability in both connection start time and duration.
- Dinner: Sessions during dinner time. Present in all time cycles with the same proportion. Low variability in both connection start time and duration.
- Home: Sessions at home, connecting during the afternoon and not necessarily leaving the next morning. Present in all time cycles. High variability in both connection start time and duration.
- Pillow: Sessions at home, connecting during the night and not necessarily leaving the next morning. Present in all time cycles. Low variability in connection start-time but high variability in connection duration.
- Shortstay: Short sessions (less than 2 hours on average) in the city. More present during working days than weekends. High variability in connection start time but low variability in connection duration.
- Visit: Sessions in the city throughout the day. More present during weekends than working days. High variability in both connection start time and duration.
- Worktime: Sessions during working time. More present in Workday time-cycle than on Fridays, and not present on weekends. Low variability in both connection start time and duration.

On one hand, in the case of the Worktime, Commuter, Home and Pillow profiles, the number of flexible hours is highly considerable. However, the distinction between Commuter and Home users is precisely to differentiate between users with high variability and users with a more regular and reliable (in terms of flexibility) pattern. On the other hand, in all data sets it can be observed that the general charging time is similar for all user profiles, with the exception of Shortstay users whose charging time is limited by the connection time (i.e. disconnection before reaching the 100% of charge).

Figure 6.1 illustrates the centroids of all clusters found in the Arnhem and Amsterdam data sets, defined by the connection start hour and the connection duration. This figure clearly shows that user profiles like Worktime, Commuters or Dinner have a common pattern between these cities and the centroids of the clusters have considerable similarities. On the other hand, Shortstay, Visit and Pillow profiles are also similar between cities but show more variability. Finally, Home profile draws a certain bias between cities: Arnhem clusters seem to have a lower connection time compared to Amsterdam clusters.

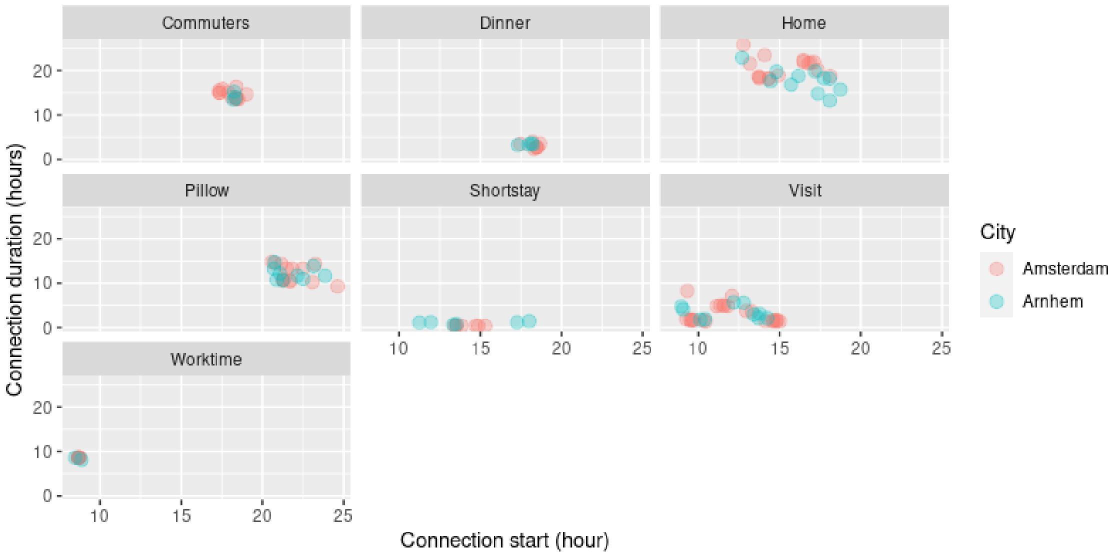

Figure 6.1: Comparison of clusters' centroids between Amsterdam and Arnhem

6.2 Modelling and simulation of EV user profiles

The journal article presented in Chapter 4 introduces the methodology for modelling the EV user profiles previously clustered. This methodology is later improved in the journal article presented in Chapter 5, where the energy models are then built per charging rate and user profile separately instead of a single energy model per user profile (as initially done in Chapter 4). This improvement was introduced in the methodology after realising the relevant differences between the density distributions of energy for every different charging rate, as shown in Figure 6.2, especially the vehicles charging at 3.7kW (i.e. single phase, 16A) and user profiles with short connection times like Shortstay and Dinner (i.e. connection duration limits the energy charged).

The actual result of the modelling methodology is an EV model composed of multiple time cycles (e.g. day of the week), each one with its corresponding user profiles models, at the same time composed of multiple bivariate MM for the connection variables (i.e. start time and duration) and univariate MM for the energy variable. The creation of this EV model is done by functions from the `evprof` R package [7] and can be stored as an R object (i.e. RDS extension) or in a JSON file. Figure 6.3 shows an example of the contents of the Amsterdam model JSON file.

The `evsim` R package [8] allows simulating EV charging sessions from the `evprof` EV model. In the journal articles from Chapters 4 and 5 these simulations resulted in EV charging sessions data sets representing the EV user profiles in every case. For example in Chapter 5, the simulation was done according to the number of

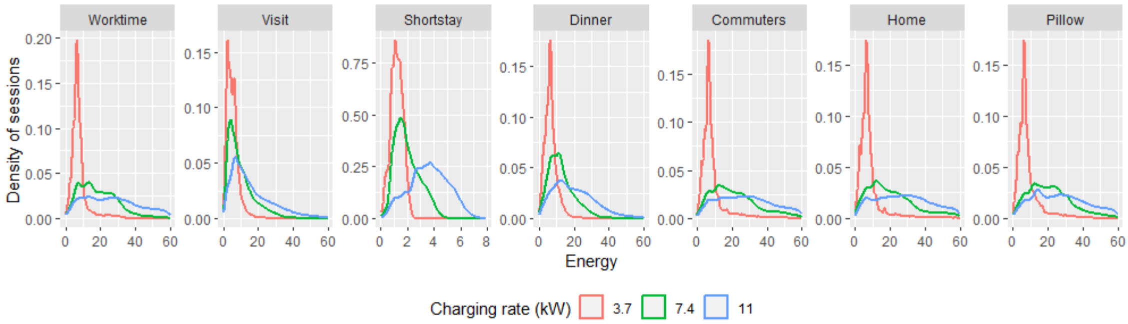

Figure 6.2: Density curves for energy values of sessions belonging to every user profile and charging rate in Amsterdam

charging sessions per week in every low-voltage transformer, but also considering the distribution of user profiles in the district supplied by the transformer. Simulating EV demand at a district level based on user profiles provides an accurate estimation of the demand peaks and power profiles.

6.3 Charging infrastructure planning

In this thesis, the charging infrastructure planning has not been a contribution itself but a result of implementing the methodologies developed. Two different scenarios of planning charging infrastructures have been analysed: a small charging hub and a city-level charging infrastructure.

6.3.1 Sizing of a charging hub

The journal article presented in Chapter 4 simulated the charging sessions in a charging hub, considering different values of the number of sessions per day (N) in a range from 1 to 24, the number of charging points (P) in a range from 1 to 25 and the maximum connection hours (H) in a range from 1 to 24. Two different assessment scenarios for an undersized charging hub with 8 charging stations are presented in the article: (1) connection time limitation and (2) expansion of the charging hub.

In the second scenario, the optimal number of charging stations is assessed for a balance between the required investment and EV user satisfaction. It is obvious that oversizing the charging hub will always provide a good charging service during the following years, but the required investment must fit under the business model in the short term. With this purpose, a custom metric "ChargingHappiness" was designed to quantify this balance between the charging hub investor and the charging service

Figure 6.3: Screenshot examples from an `evprof` model JSON file

provided to EV users.

The actual result of this work is a graph that shows the optimal number of charging points given the expected number of sessions per day and a minimum accepted ChargingHappiness, which in this case was considered to be 0.75. For the Borg's harbour with a current number of 8 charging points, installing 5 more charging points (13 in total) would suppose a ChargingHappiness between 0.75 and 0.8 in demand scenarios up to 19 sessions per day.

Of course, these numbers are for this specific use case with the corresponding user profiles that define a specific distribution of sessions over the day. In that sense, modelling and simulating the charging sessions by user profile is crucial to obtain accurate results for a specific study case.

6.3.2 Sizing of a city-scale infrastructure

The journal article presented in Chapter 5 simulated the charging sessions downstream of 9 different low-voltage transformers, located in different districts of the city, and 7 different scenarios of EV penetration, each one corresponding to a multiplying factor "k" from 1 to 7 to the current number of sessions per week.

The required number of charging points has been calculated for every growing scenario. Figure 6.4 shows that almost half of the low-voltage transformers (i.e.

9006775, 9015800, 3002819 and 3006277) will need more charging points with twice the current EV demand (i.e. k=2), and practically all transformers will need more charging stations with three more times the current EV demand (i.e. k=3).

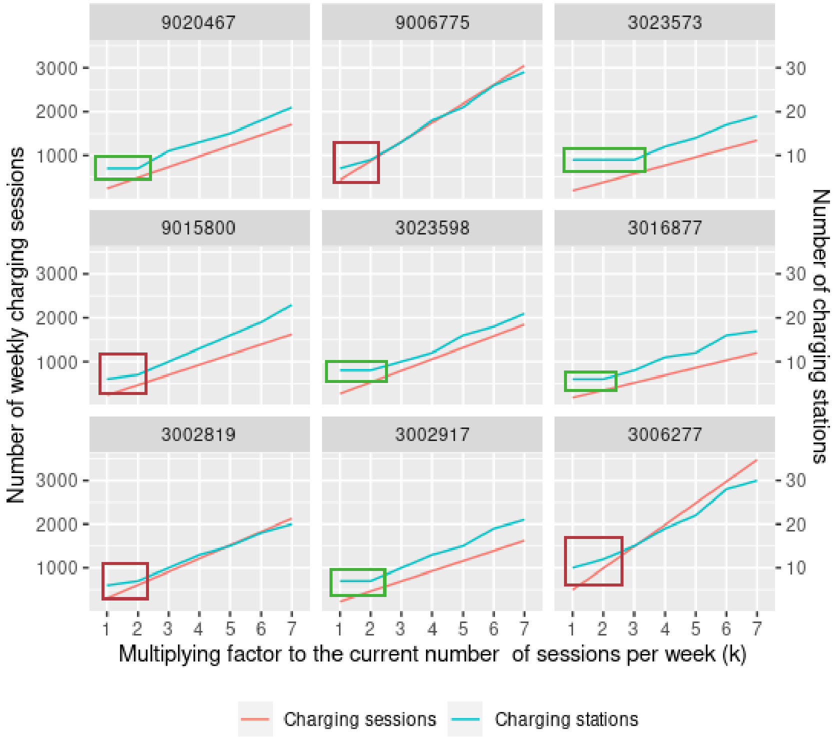

Figure 6.4: Charging infrastructure growth according to sessions/week per transformer

This is an important point since a general problem in Amsterdam's power grid is that the DSO can't allow installing more charging stations in some districts because of grid congestion. This is a severe issue for the Municipality and its carbon-neutral objectives for the near future. Therefore, as presented in the next section, Flexpower is going to be crucial to cope with this challenge and enable the installation of more charging stations (i.e. higher penetration of EVs) under the same grid capacity and deferring grid upgrades.

Another observation from the results illustrated in Figure 6.4 is that the growth of charging stations (blue line) is not directly proportional to the growth of charging sessions (red line). This relation depends on the distribution of the user profiles and the number of EV users aiming to charge around the same time. This also validates how crucial it is to model and simulate the EV demand based on the characteristics of the area at issue.

6.4 Flexibility management of electric vehicles

As EV adoption continues to grow rapidly, the ability to harness the inherent flexibility of these vehicles becomes crucial for ensuring grid stability, optimizing energy management, and enabling the effective usage of renewable energy resources and charging infrastructure. This thesis aimed to develop algorithms to simulate some of the most common strategies to take advantage of EV flexibility.

6.4.1 Postponing charging sessions

The first article, presented in Chapter 3, raises a smart charging program where individual sessions are postponed in time in order to optimize the aggregated EV power profile. The focus of the simulation is to compare the performance of the smart charging program with and without classifying EV sessions into different EV user profiles. To make this comparison three distinct indicators were used: percentage of peak reduction respective to original static demand, percentage of sessions postponed and percentage of energy consumed from the grid (i.e. imported energy). The main result from this comparison is that, while the peak reduction and the imported energy have similar values in both smart charging programs, the percentage of sessions postponed is double when not using the EV user profiles extra-knowledge.

In a practical example, the use of EV user profiles could be translated into lower exploitation costs of the flexibility mechanism or a lower impact on the final EV user. At the same time, the required new function to use the smart charging system presented would be a system to classify every EV user (i.e. car ID) into a certain user profile. This would let the Charging Point Operator (CPO) know which charging sessions to postpone or not. Of course, this approach assumes that one EV user corresponds to one user profile. This assumption could not be valid for all charging sessions of an EV user profile depending on the variability of his/her behaviour. The hypothesis could not be validated because none of the charging sessions data sets included the identifier of the vehicle due to privacy issues. However, it is logical to assume that every EV user will have a predominant connection behaviour that will define his or her user profile and that this methodology could be potentially applicable by the CPO.

6.4.2 Limiting connection time

In the second article, presented in Chaper 4, EV flexibility management is not explicitly controlled by a CPO or an aggregator. In this case, the flexibility of the EV users is exploited in the time dimension, limiting their connection time in order to make the charging points available to other EV users. This simulation assumes that all EV users respect the rules to avoid some kind of fine or penalty, like the existing parking control on the public roads of cities. This type of regulation of the charging infrastructure is usual in charging hubs where the number of charging points is limited respectively to the number of EV users. The paper refers to this situation as an undersized charging hub.

It is actually a very basic method, but the goal of developing this algorithm was to analyse the impact of this type of regulation that constitutes a common limitation of the charging infrastructure usage in all places where the charging infrastructure can not be expanded. When introducing a limit on the connection time, it is crucial to consider the average charging time to avoid impacting the user. If the connection time limit is too low for the users' requirements, the regulation will prevent the vehicles from charging all their energy requirements. This could result in a loss of confidence in the charging infrastructure by the clients.

The results show that the type of EV user is highly important when applying this regulation. In order to be a useful measure, the EV users must be distributed over the day ensuring that the released charging points will be used by incoming EV users. If this is not the case and all users arrive around the same time (e.g. charging hub in an office building, school, etc.), this type of regulation will not increase the satisfaction of EV users nor optimize the utilization of the charging infrastructure. In those cases, the only way to allow all EV users to charge is to expand the number of charging points and limit the charging power to avoid a demand peak. This strategy is discussed hereunder.

6.4.3 Curtailing charging power

The journal paper presented in Chapter 5 presents an algorithm to simulate the application of curtailing charging power based on dynamic capacity signals (15-minute resolution) sent by the DSO to the CPO. This algorithm represents the Flexpower3 pilot project implemented in the public charging infrastructure of Amsterdam.

In each one of these 7 scenarios, the business-as-usual simulated EV demand is compared to the optimal demand obtained with the application of the Flexpower algorithm. An example of these simulations is shown in Figure 6.5, where the green-shaded line represents the flexible EV demand and the static (or business-as-usual) demand is represented by the darkgreen-dashed line, while the red-dashed line represents the transformer (MSR) capacity limits set by the DSO.

From Figure 6.5 we can extract multiple outcomes. First, the transformer capacity is curtailed based on the rest of the power demand existing in the district (i.e. households, offices, etc.). For this reason, there are more constrained hours

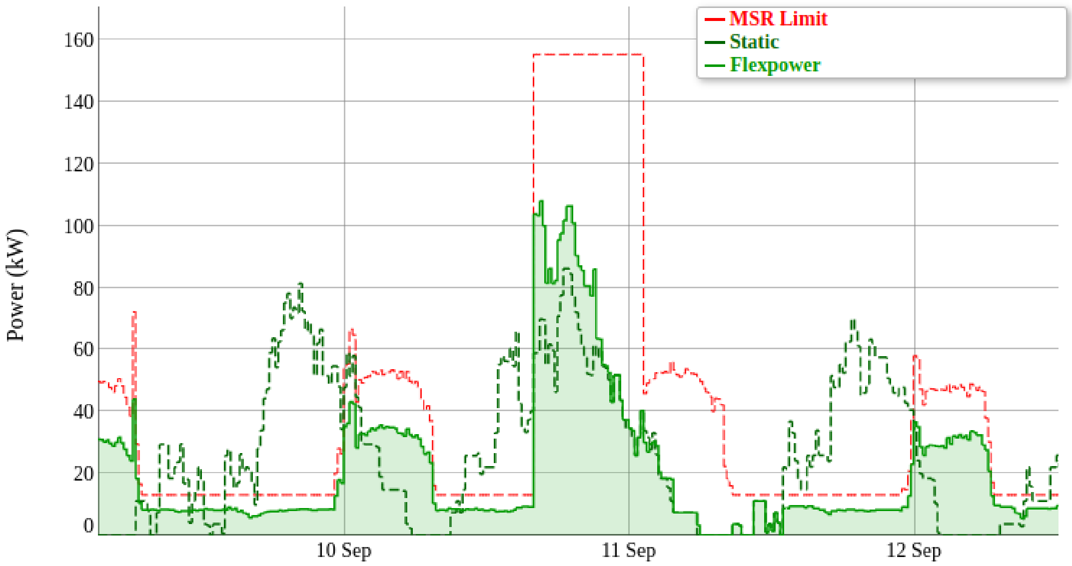

Figure 6.5: Curtailment of charging power simulation based on dynamic grid capacity limits

(e.g. daily activity hours) and less constrained hours (e.g. night hours). It is visible that on the 10th and 12th of September the afternoon load is shifted to the night, while on the 11th the afternoon is not constrained and the maximum capacity of the transformer is allowed. This causes a rebound effect since the flexible demand gets larger than the static demand, moreover during peak hours. Obviously, this would not suppose a problem while the total demand keeps being lower than the transformer capacity, but it shows that the EV demand is highly susceptible to the dynamic signal sent by the DSO if it has been previously constrained. This means that the DSO must forecast with high confidence the power load from the rest of the system in order to accurately define the reserved capacity for the EVs.

Another important aspect visible from Figure 6.5 is that, when limiting the charging power, there is a gap between the maximum capacity allowed (red line) and the maximum flexible demand (green-shaded line). The transformer capacity is shown in kW considering the three-phase power system, while the Flexpower limitation is defined by maximum amperes per phase. This causes an over-limitation of the EV demand since the system considers the worst-case scenario where all single-phase vehicles are connected to the same phase. If all vehicles had a three-phase connection, the gap would disappear and the smart charging system would become much more efficient. However, the Flexpower system has no option to smartly distribute the single-phase or two-phase vehicles among the different phases.

Concretely the charging rate is also a reason for concern about Flexpower impact. The hypothesis that vehicles charging at lower rates (e.g. 3.7kW) were more impacted than users charging at higher rates (e.g. 11kW) has not resulted significantly true. This is because the users charging at higher rates also consume more energy, and we can see similar results by calculating the percentage of energy that could not be charged due to power limitation relative to the total energy required by the user. However, we could definitely see a difference in the final user impact by user profile. The most affected user profiles were Shortstay, Visit and especially Dinner, since Dinner sessions occur during peak hours and have a short connection time. This draws an opportunity to include the user-profiling approach within the Flexpower project. The CPO could set a rule to override power limitations depending on the user profile, if this information was available beforehand. This feature could decrease the impact on the EV user service with a high level of confidence by the CPO.

Chapter 7

Conclusions

This thesis contributes significantly to three key areas within the realm of the electric vehicle (EV) transition: clustering and modelling of EV user profiles, flexibility management strategies for EV demand, and the planning of charging infrastructure to facilitate the increasing adoption of EVs. The following are the main conclusions and further work derived from the results presented in this thesis.

Clustering EV user profiles: a methodology for clustering EV user profiles has been presented, contributing to achieving objective O1. Following, the key findings from the development of this clustering methodology are described.

- Gaussian Mixture Models (GMM) clustering technique, considering the stochastic nature of EV user behaviour, has resulted in a successful method to discover underlying trends and similarities among EV users.
- Pre-processing steps such as logarithmic transformation and outlier cleaning improved the accuracy of GMM clustering results and cluster determination.
- Distinct user profiles were identified based on the interpretation of cluster characteristics, including connection start time, duration, and the shape of covariance ellipses. Including the variance variable in the profiling step helps the data analyst to differentiate between potential flexible sessions for smart charging programs.
- Common usage patterns in public charging infrastructure, such as Commuters, Dinner, Home, Pillow, Shortstay, Visit, and Worktime, were observed across different data sets, providing valuable insights into EV user behaviour.
- The user profiles between Arnhem and Amsterdam resulted to have relevant similarities. This brings the option to build a general “Dutch” or “European” EV model usable for a wide range of use cases.

- Further work: create a method to automatically find the optimal number of clusters for a determined data set. Currently, the BIC approach is useful but still it is a manual process which requires a lot of analysis time for choosing the balance between the number of clusters and the BIC score (to avoid overfitting).

- Further work: validate that each vehicle corresponds to a single user profile in most of its sessions. It is a reasonable assumption, but it has to be validated with a data set that provides the vehicle ID (unfortunately this was not the case in this thesis due to privacy issues)

Modelling and simulation of EV user profiles: a methodology to model and simulate EV user profiles has been presented, contributing to achieve objective O2. Following are the key findings from the development of the models and the execution of EV demand simulations.

- The development of EV models based on user profiles facilitated the creation of multi-time cycle models, considering connection variables (start time and duration) and energy variables separately.

- The charging power is a variable that highly influences the energy consumption of the electric vehicle. The higher the charging power, the higher the energy demand. This is because the market trend of new EV models is to have a larger battery but also allowing to charge the vehicle at higher power rates to decrease the charging time.

- The accurate modelling and simulation of EV demand based on user profiles are crucial for estimating accurate EV demand results for specific study cases that require a certain typology of EV users.

- Configuring the specific presence from each user profile resulted in crucial to provide accurate estimations of EV demand peaks and simultaneity of charging sessions, supporting the sizing process for both small charging hubs and city-scale charging infrastructure, emphasizing the importance of modelling and simulating EV demand based on area characteristics.

- Further work 1: If the new EV models charging at 11 kW consume more energy, probably this will suppose charging less often. The probability to shift the charge to the next day should be considered in the simulations since it would result in a not-so-exponential increase in EV energy demand. However, this needs to be validated with a data set containing the vehicle ID variable in order to track the charging sessions of every vehicle (data not available for this thesis).

- Further work 2: Applying the modelling approach to more different use cases could bring the opportunity to create a generic EV model that could be applied generally in other cities outside the Netherlands. The identification of common user profiles across cities would be an interesting task to properly simulate the EV demand in any use case.

- Further work 3: Currently, the BIC criterion defines the optimal number of clusters but the distribution and shape of clusters depend on the random seed of the EM algorithm. A visual supervision process is currently required at this step of the clustering methodology, so an important improvement would be to automatically detect the random seed that provides the optimal distribution of clusters.

Flexibility management of EV: the algorithms to simulate different smart charging strategies have been developed, contributing to the achievement of objective O3. Following are the key findings from the simulation of such algorithms.

- Smart charging programs leveraging EV user profiles resulted in a lower percentage of postponed sessions, leading to potential cost savings and reduced impact on EV users.

- The decision of exploiting a charging sessions based on its user profile assumes that the vehicles correspond to a single user profile. This is highly probable for most users but must be proven in further works.

- Limiting connection time as a regulation method in undersized charging hubs proved effective when EV users were distributed throughout the day, optimizing charging infrastructure utilization.

- When introducing a limit on the connection time, it is crucial to consider the average charging time to avoid impacting the user.

- The application of curtailing charging power based on dynamic capacity signals from the DSO demonstrated the effectiveness of the Flexpower3 pilot project in Amsterdam's public charging infrastructure.

- The analysis of city-level infrastructure highlighted the need for more charging stations with the growth of EV demand, particularly in some transformers, which means that a wider implementation of Flexpower will be essential in the near future of Amsterdam.

- Further work: development and publication of a documentation website for the flextools R package, now available in Github [9]

In conclusion, this thesis provides valuable insights into EV user behaviour by clustering and modelling EV user profiles, as well as simulating smart charging strategies for flexibility management and charging infrastructure planning. Moreover, the integrated modelling and simulation framework provided by the open-source R packages `evprof` and `evsim` is an added value to ensure the reproducibility of this work. Overall, this research aims to provide a broader understanding of the electric vehicle transition by offering practical implications for stakeholders involved in the EV ecosystem.

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