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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).

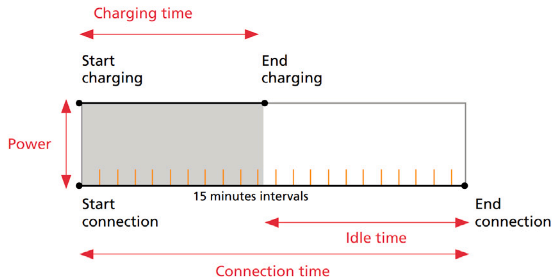

Fig. 1. Parameters of a charging session.
Source: HvA (van den Hoed et al., 2019).

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     $ConnectionEndDateTime = ConnectionStartDateTime$ for sessions that start in $dttmSeqFull[i]$

    $ChargingEndDateTime = ChargingStartDateTime$ 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

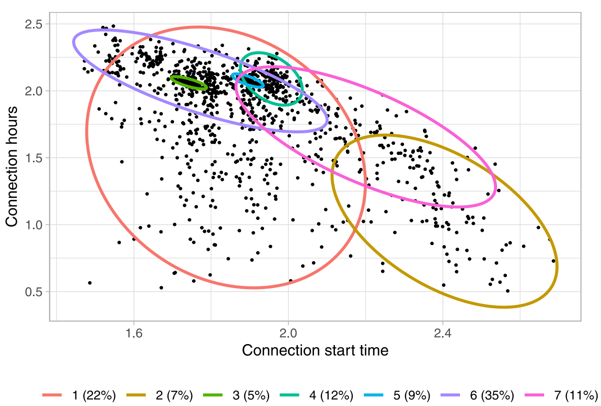

Fig. 2. Cluster for different day-sessions.

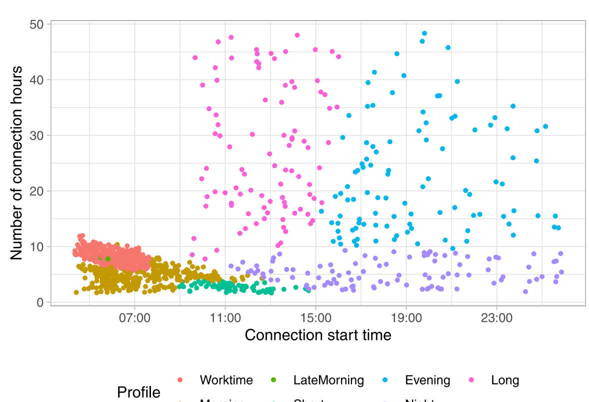

Fig. 3. Final sessions' classification among user profiles.

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.

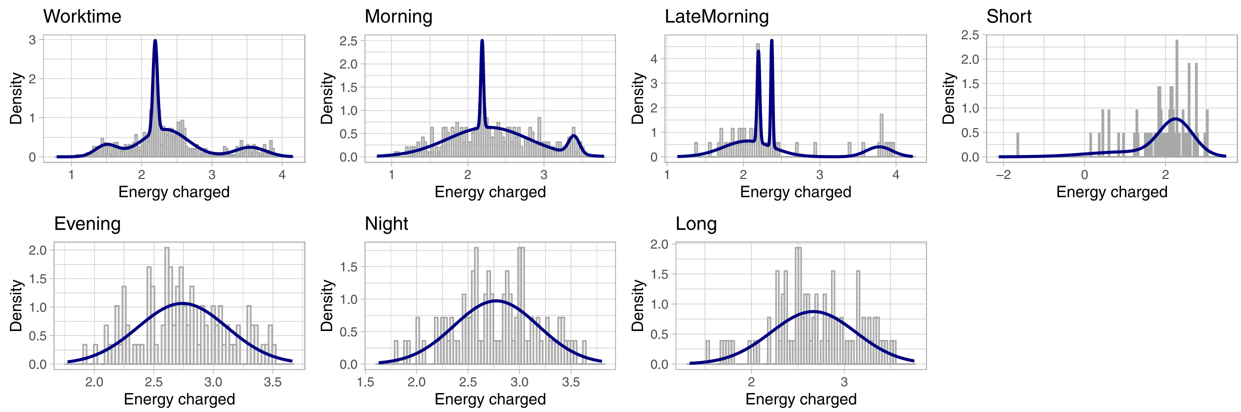

Fig. 4. Density values histogram and the density distribution from the Gaussian models.

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

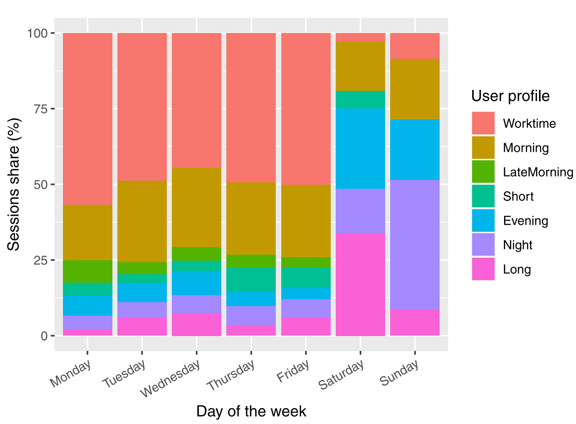

Fig. 5. Share of user profiles by day of the week.

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

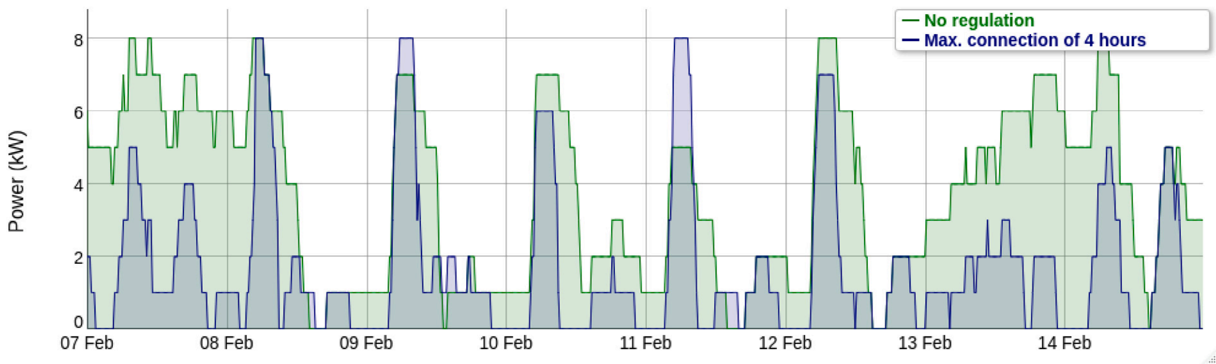

Fig. 6. Example of occupancy simulation without regulation (green) and $H = 4$ h (blue).

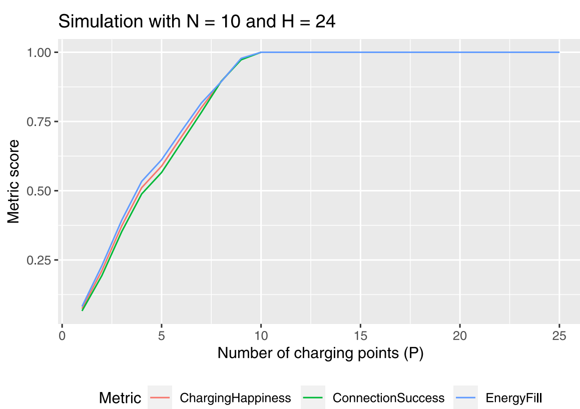

Fig. 7. Simulation for $N = 10$ and $H = 24$.

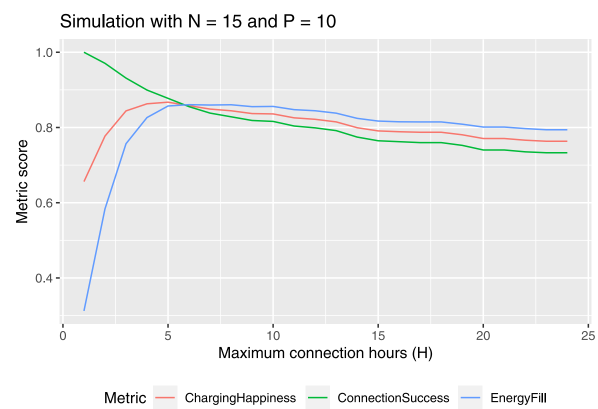

Fig. 9. Simulation for $N = 15$ and $P = 10$.

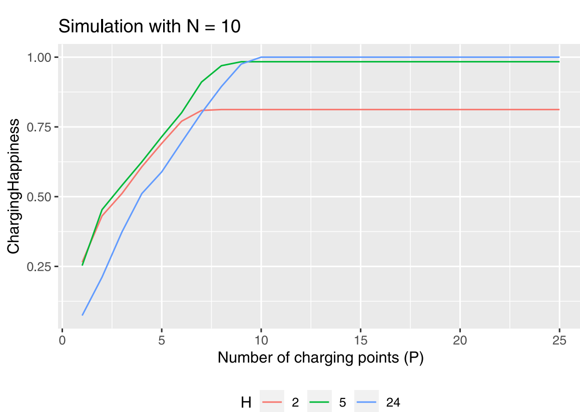

Fig. 8. Simulation for $N = 10$.

$ConnectionSuccess$ 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

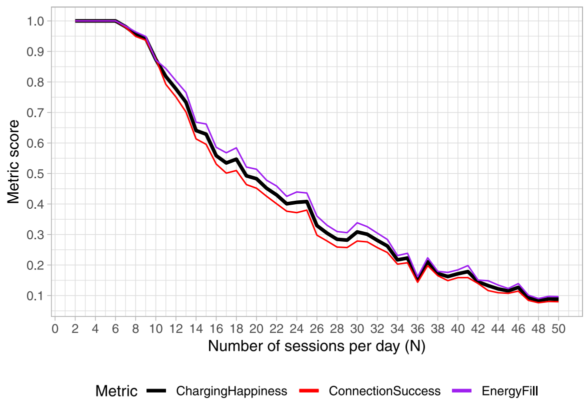

Fig. 10. Baseline with $P = 8$ and no regulation ($H = \infty$).

$ChargingHappiness$ 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.

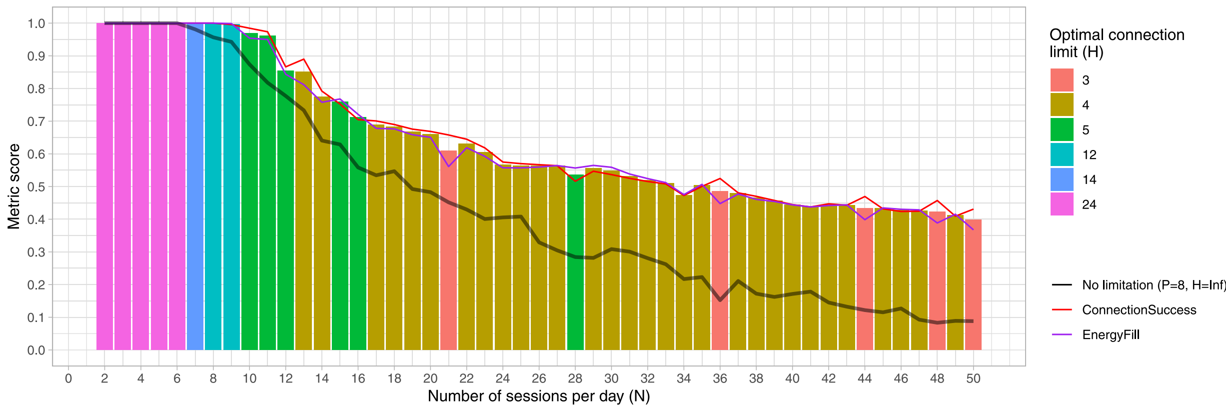

Fig. 11. $ChargingHappiness$ for a charging infrastructure with $P = 8$.

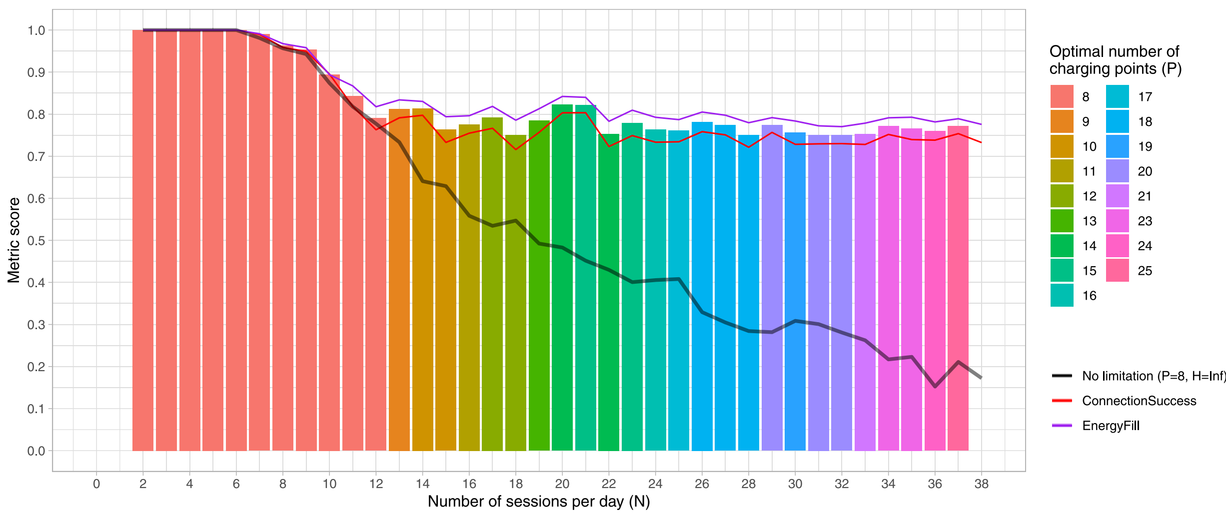

Fig. 12. $ChargingHappiness$ for a charging infrastructure without connection limit.

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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