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Electric vehicle charging sessions generator based on clustered driver behaviors

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Executive Summary

The increasing penetration rate of electric vehicles (EV) requires the installation of new charge points, which can induce various problems, such as higher peak powers. To address these problems, a well-known approach is to use simulations to assess the impact of uncoordinated charging on a particular local energy system. Such simulations require EV charging sessions data which are often not (sufficiently) available. This paper proposes a methodology that generates EV charging sessions based on statistical parameters of different type of EV drivers, which have been extracted from historical data via data mining techniques. The results show the great ability of the methodology to generate representative charging profiles for different types of drivers. Additional scenarios are simulated to show the strong impacts of uncoordinated charging for the use case of a hospital.

Keywords: Charging, Demand, Energy security, Power, User behaviour

1 Introduction

In a Sustainable Development Scenario (SDS) 2020-2030, the EV market share is expected to grow exponentially up to 13.4% in 2030 [1]. Consequently, there will be a need to install or expand charging infrastructures at different locations (residences, office buildings, hospitals, etc.). This must be done in a controlled way by assessing the potential impacts on electric systems, and to act accordingly in case of emerging problems. In scientific literature, simulations show that the addition of new charge points will impact the electric grid on different levels, from local energy systems (LES) [2] to distribution and transmission system operators (DSO and TSO) [3]. Solutions to these problems are already strongly studied and often presented in simulations. There exist multiple solutions to the problem of adding charge points, but two are of great interest; a) adapt the design of electric system by reinforcing it, b) charge in an intelligent manner (smart charging or vehicle-to-grid) [4].

While simulations are of great interest to anticipate future problems and even find solutions to these future problems, they require accurate data and models to make them work. In particular for EVs, simulations usually need EV charging sessions data. These EV charging sessions data consist of arrival and departure time, the charging demand and the charging power. Unfortunately, such data are not commonly available or sometimes are partially available. In addition, for the design of new charging locations, new charging sessions are expected, hence new charging sessions data need somehow to be generated/predicted.

To generate plausible EV charging sessions, some tools have already been developed in literature. Authors in [5] developed a tool that generates time series of vehicle mobility, driving consumption, grid availability and grid electricity demand. The input parameters are numerous, ranging from EV driver information to EV characteristics and charge point information. Such input data are usually unknown for new charging locations, for instance, when a site wants to design or expand its charging location. Authors in [6] adapted a "Remote-Areas Multi-energy systems load Profiles" (RAMP) software engine, from [7], for stochastic EV driver behaviour simulation. The simulator uses EV driver data from surveys to classify the behavior into default groups such as student, workers and inactive users, but also into small, medium and large EV sizes. This methodology has been designed to simulate mass-scale deployment of EVs on a country-level, which is not suited for smaller charging locations. To simplify this, authors in [8] generated EV charging sessions based on probability density functions (PDFs). Typically, arrival and departure time are based on Gaussian distributions and the daily mileage is based on log-normal distributions. However, this methodology lacks accuracy when dealing with different type of EV drivers because it assumes one probability density function for all drivers.

The key contributions of the EV charging sessions generator proposed in this paper, compared to other existing ones from the literature, are:

- Classifying EV drivers by clustering features of historical charging sessions of the drivers. Using statistical parameters (probability distributions) of the features per clusters allow to reproduce charging sessions for different type of EV drivers.
- The ability to apply the method easily to data from different local energy systems (office buildings, shops, houses, etc) can help to investigate/design different use cases.
- The modularity of the generator, its ease-of-use and the standardized output data format are key attributes of its scalability and replicability.

The paper is organized as follows. The methodology of the charging sessions generator is explained in section 2. This generator will be tested on a use case which is presented in section 3.1 and analyzed in section 3.2. To illustrate the benefit of using the generator, the impact of uncoordinated charging is simulated and presented in section 3.3.

2 Methodology

The methodology proposed in this paper is illustrated in the scheme shown in Fig.1. It consists of mainly two parts; a first part on historical data analysis and clustering that is detailed in section 2.1, and a second part on the generator that is detailed in section 2.2.

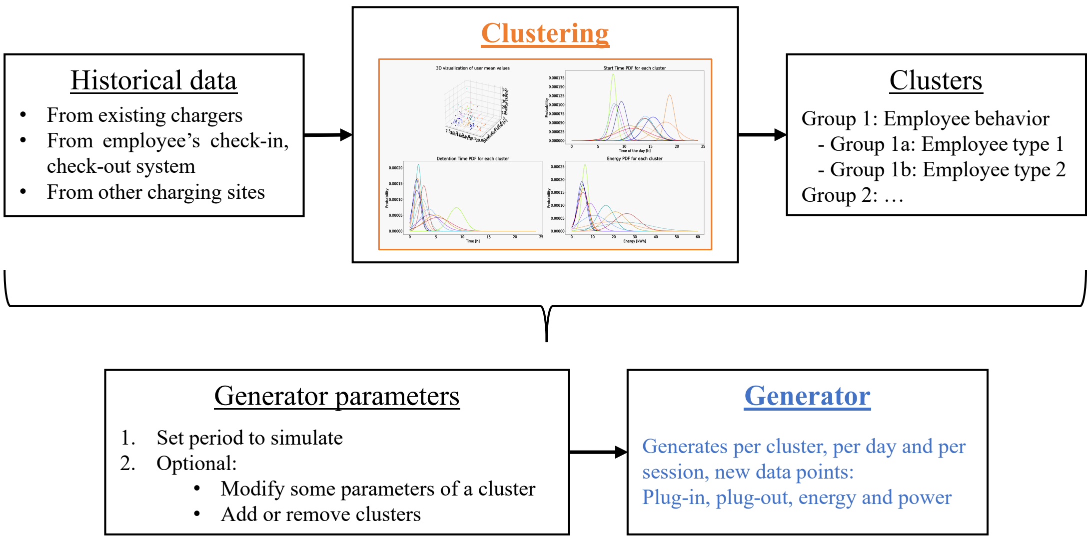

Figure 1: Scheme of the methodology of the generator

2.1 Clustering

The objective is to group (to cluster) EV drivers with a similar charging behavior in order to extract important statistical parameters to build probability distributions. These probability distributions will be the baseline to generate new charging sessions. The clustering proposed in this study works in two levels. A first clustering is performed on the charging sessions features, followed then by a second clustering on the frequency of charging of an EV driver. Since such clustering relies strongly on the data points used, which include a set of features, a data pre-processing is done.

2.1.1 Features used to cluster

The dataset consists of individual charging sessions where each of them contains four different features; a) an identification, b) a plug-in time, c) a plug-out time and d) an energy consumed. These features are usually available since they are used in the communication standard “Open Charge Point Protocol” (OCPP) between charge points and the charge point operator (CPO) [9]. These charging sessions data are required in order to bill a charging session to an EV driver (using Charge Detail Record (CDR) in OCPP).

The aim of the clustering is to group EV drivers (with their corresponding charging sessions). However, it is mathematically impossible to cluster the identification feature. Consequently, a technique is used to replace all charging sessions from an individual EV driver to one specific theoretical charging session. The method consists of computing the mean value of the plug-in times, the parking times (where parking time is the difference between plug-in and plug-out times) and the energy charged, of all the charging sessions of an EV driver. This ends up with one theoretical charging session per EV driver consisting of only mean values.

Once the first three parameters have been clustered (mean plug-in time, mean parking time and mean energy), a second clustering is performed to differentiate regular EV drivers from occasional ones. One would cluster the number of charging sessions of an EV driver. However, it has a limitation because it does not include the period where these charging sessions happened. For instance, an EV driver that charged 20 times in 20 days can be in the same cluster as an EV driver that charged 20 times in 200 days. To include this aspect in the second clustering, the frequency of charging is clustered instead of just the number of charging sessions. The frequency of clustering, denoted $freq$, is defined in (1).

$$freq = \frac{\text{Number of charging sessions}}{\text{Period between first session and last day of the dataset}} \tag{1}$$

The period in the denominator includes the last day of the dataset and not the last day of an EV driver session. This solves an issue for EV drivers that came only once. The frequency is theoretically one, hence 100% probability of having a session per day, which does not make sense for a unique session.

2.1.2 Clustering algorithm

There exist multiple techniques to group charging sessions. A well-known approach is an unsupervised machine learning technique called clustering. Among the numerous clustering algorithms in the literature, the most common one is the k-means clustering. In-depth explanation on the working principle of k-means clustering can be found in [10]. Examples of clustering of charging sessions using k-means algorithm can be found in [11], [12], [13] or [14]. The k-means algorithm requires the number of clusters as input to cluster. Since it is unknown how many clusters there are, different metrics are used from literature to help identify the correct number of clusters, which are the elbow method and the Davies-bouldin score.

2.1.3 Statistical parameters

Once the charging sessions have been clustered together, some statistical parameters are extracted to build probability distributions. The main statistical parameters and distributions which are extracted per cluster are listed hereunder.

- The probability of having a certain number of charging sessions per day. It has been decided to divide this probability into two discrete probability distributions, mainly one for the working days and one for the weekend days, since the number of session are highly different.
- The probability of having an EV plug-in and plug-out at a certain time. These probabilities are also represented by two discrete probability distributions.
- The probability of having a certain amount of energy to charge. This probability is represented by a Gaussian distribution, where the mean and standard deviation are used.

2.2 Generator

The EV charging sessions generator principle is show in Algorithm 1. It requires two inputs: the period over which to simulate and the probabilities of the features per cluster. Using this information, the generator works in two main steps:

- Step 1) For each cluster, and for each day to simulate, a function (called f1) determines the number of charging sessions to generate.
- Step 2) For each charging session to generate, two functions (called f2 and f3) determine the plug-in and plug-out time, and the energy to charge.

Algorithm 1 : EV charging session generator

```
Input: Simulation dates, clusters data
for all clusters do
    for all simulation dates do
        f1: Get number of sessions
        for all sessions do
            f2: Get plug-in and plug-out time
            f3: Get energy
Output: Generated charging sessions
```

The first function (f1) chooses a certain number of charging sessions for the day and cluster selected. It will select randomly a number of sessions based on the discrete probability distribution of the frequency feature for a cluster. Similarly, the second function (f2) chooses a plug-in and plug-out time based on the discrete probability distributions of those features. With function (f3) two values are created: a) the maximum energy that can be charged considering the maximum charging power of the charger during a parking time determined with (f2), b) a random energy selection based on the Gaussian distribution of the energy feature of the cluster. This is done to verify that the energy generated for the session is lower than the maximum energy that can be charged.

3 Results

3.1 Use case

The charging events have been recorded from a charging location inside the parking lot of a hospital in Brussels. It is an open-access charging location, with paid parking fee. It consists of six charge points containing two Type 2 (IEC 61851) connectors, hence maximum 12 connectors, delivering up to 22 kW each. The charging sessions have been logged between May 2018 and February 2020. This period corresponds to 3922 charging sessions and 179 different EV drivers. To have a better understanding on the use case under study, Fig.2 shows a differentiation between EV drivers with unique charging sessions and EV drivers with multiple charging sessions. It can be observed that two-thirds of the EV drivers that charged represents only 5 % of all the charging sessions.

3.2 Clustering results

The first step is to cluster the plug-in time, the parking time and the energy charged. Using the elbow method and Davies-bouldin score, the number of clusters has been set to 8 clusters. The two methods are shown in Fig.3.
The elbow method indicates the optimal number of clusters to be 8 clusters (elbow of the curve on Fig.3). The Davies-Bouldin score shows a similar result of 8 clusters (lowest score on Fig.3). To have an idea on how EV drivers differ and are grouped, the first clustering is represented in Fig.4 with probability density functions and a three-dimensional representations for the three main features. As explained previously, the features represent EV drivers mean values and not individual charging sessions.
Figure 4 shows the different PDFs for the different clusters. Thanks to this, it becomes easy to differentiate the behavior of certain type of drivers. For instance, cluster 2 and cluster 3 have a similar plug-in time (early in the morning), a different parking time (cluster 3 parking time is shorter), but still a similar energy needs. To have a quantitative understanding, Table 1 summarizes the characteristics of the clusters.

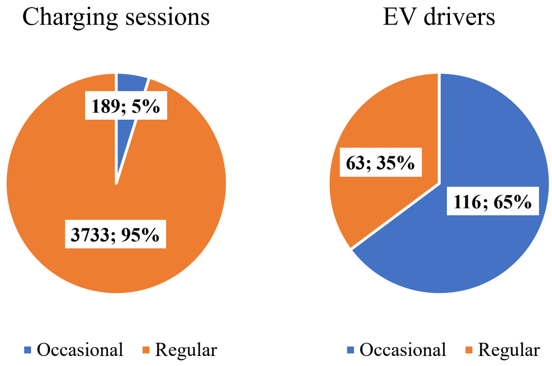

Figure 2: EV drivers and charging sessions division in regular and occasional drivers

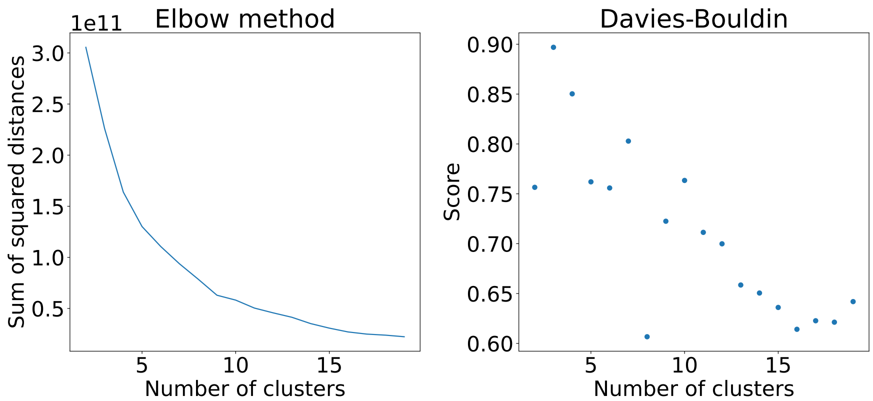

Figure 3: Number of clusters identification for k-means clustering algorithm

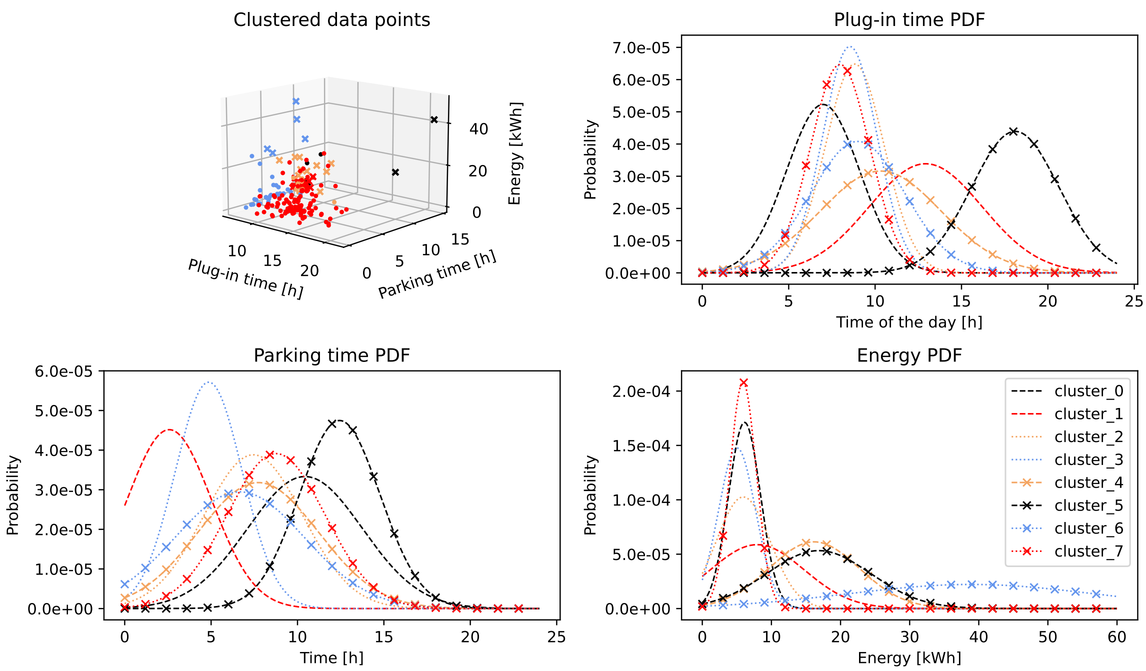

Figure 4: Results of the first clustering

Table 1: Clusters quantitative characteristics

Cluster ID	# of sessions	# of drivers	Plug-in time (mean value)	Parking time (mean value)	Energy (mean in [kWh])	Sub-clusters
Cluster 0	350	4	Morning (06h59)	Very long (10h25)	Low (6.11)	2
Cluster 1	458	105	Afternoon (12h55)	Short (02h34)	Low (7.59)	3
Cluster 2	782	10	Morning (08h49)	Long (07h26)	Low (5.92)	3
Cluster 3	419	29	Morning (08h32)	Mid (04h52)	Low (5.02)	4
Cluster 4	170	10	Morning (10h19)	Long (07h43)	Mid (16.18)	2
Cluster 5	40	2	Afternoon (18h06)	Very long (12h26)	Mid (16.83)	2
Cluster 6	39	5	Morning (09h00)	Long (06h39)	High (38.88)	2
Cluster 7	1664	14	Morning (07h58)	Long (08h45)	Low (5.89)	4

Note: Parking time: "Short" below 3 hours, "Mid" for [3-6] hours, "Long" for [6-9] hours, "Very long" over 9 hours. Energy: "Low" below 10 kWh, "Mid" between [10-20] kWh, "High" over 20 kWh.

Table 1 shows a couple of different behaviors which are interesting to analyze. First of all, the mean energies are relatively low except for clusters 4, 5 and 6. These clusters represent 9.5% of the number of total EV drivers. Such high energy needs might indicate the use of battery electric vehicles (BEV) compared to plug-in hybrid electric vehicles (PHEV). A second interesting result to discuss is the high number of EV drivers in cluster 1. These EV drivers represent typically the behavior of visitors, whom arrive in the afternoon during visiting hours and stay a short time (less than three hours). Finally, Table 1 shows high differences in behavior between clusters. Hence, it shows the importance to cluster drivers behavior.

The last column of Table 1 shows the results of the second level clustering. It indicates the number of subclusters based on the frequency of charging. The results show that most of the clusters are divided into two subclusters, mainly in low and high frequency of charging. Nevertheless, for certain clusters, the second clustering deemed necessary to have more than two subclusters because of higher divergent frequency of charging.

3.3 Generator results

3.3.1 Scenarios

Three different scenarios are tested on the use case presented previously. These scenarios are summarized hereunder.

- Scenario 0: baseline which represents the historical data.
- Scenario 1: this has as objective to generate sessions based on the same EV driver constitution (number of drivers per cluster) as the baseline in Scenario 0 . The goal is to compare the generated charging sessions with the historical data in order to validate the methodology.
- Scenario 2: increasing the number of EV drivers from cluster 0, 2, 4, 5 and 7, which represent the employees in the population, by a factor of 2. The idea is to simulate a situation where the a larger portion of employees of the hospital transition from driving a internal combustion engine (ICE) car to an EV.

3.3.2 Validation of the method proposed

In order to ensure the validity of the proposed method, this section shows the difference between scenario 0 and scenario 1. The difference is represented with a boxplot in Fig.5 containing minimum and maximum values, interquartile ranges and median values. The figure presents the three main EV charging session features, namely the plug-in time, the parking time and the charged energy. Figure 5 shows that the three features have very similar boxplot between the historical data (scenario 0) and the generated data (Scenario 1). In addition, the number of charging sessions generated is 3760, which is close to the original number of charging sessions which is 3922. The total energy demand of all charging sessions generated is 25.174 MWh, whereas the original energy demand is 27.251 MWh. Such results show the great representativeness of the methodology proposed in this paper.

The historical data of the charging sessions contain a progressive number of charging sessions between the first and last session recorded. This observation can be seen in Fig.6. As an example, 29 charging sessions were recorded in the first 20 days in May 2018 and 12 charging sessions were recorded in one day at the beginning of 2020. This progressive increase has an impact on the probabilities of having a session per day (and per cluster). Therefore, for the validation (scenario 1), the generator takes this into

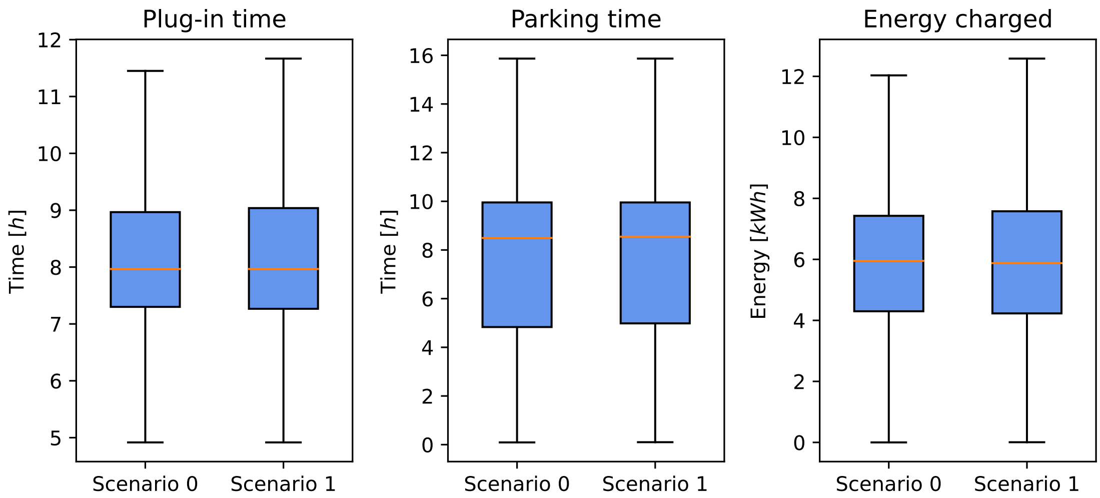

Figure 5: Comparison between historical data (Scenario 0) and generated data (Scenario 1).

account by increasing number of EV drivers per cluster over time based on the first charging session of each EV driver in the cluster observed in the data set. The good match between the baseline and scenario 1 precisely demonstrates the power of the generator as a tool to model future EV transition scenarios. By projecting new EV drivers on site (due to e.g. transition from ICE vehicles, company growth,...) these drivers can be added to existing clusters according to their group identity (employees, visitors,...) or existing mobility pattern (arrival and departure time, travelled distances,...), and sessions can be generated accordingly. Scenario 2 is an example of such a transition scenario and will be discussed in Section 3.3.3 below.

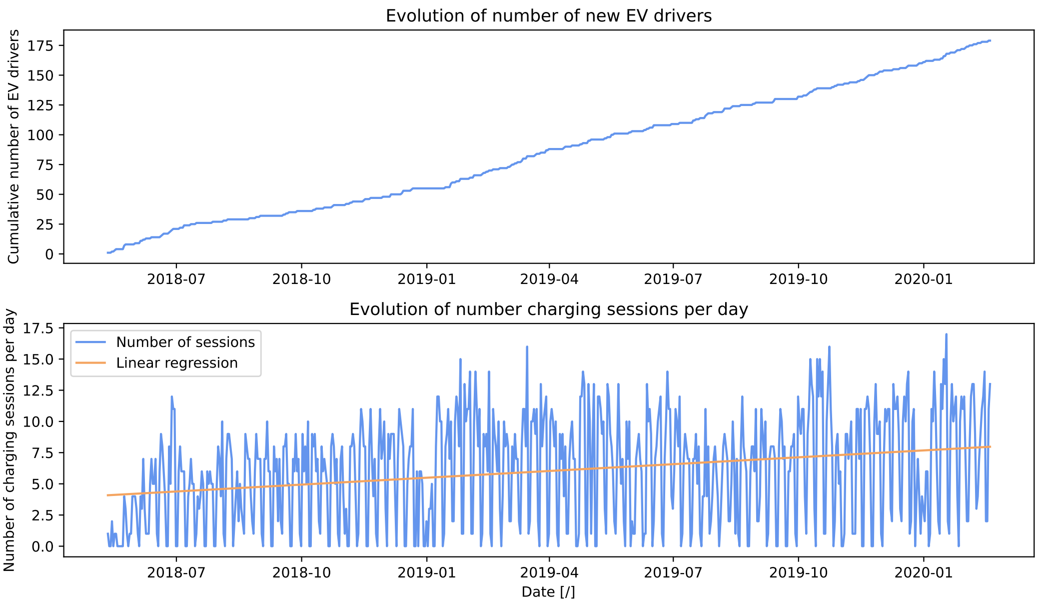

Figure 6: Evolution of the number of charging sessions for the hospital use case.

3.3.3 Uncoordinated charging simulations

To visualize the results of the generated EV charging sessions data for each scenario, uncoordinated charging is simulated. Uncoordinated charging is the current charging method where an EV is charged at maximum power directly when it is plugged-in, until fully charged. To show the uncoordinated charging power profile dynamics, Fig.7 is build by taking, for each quarter hour, the mean values, 1^{st} and 3^{rd} quartiles values and the maximum values.

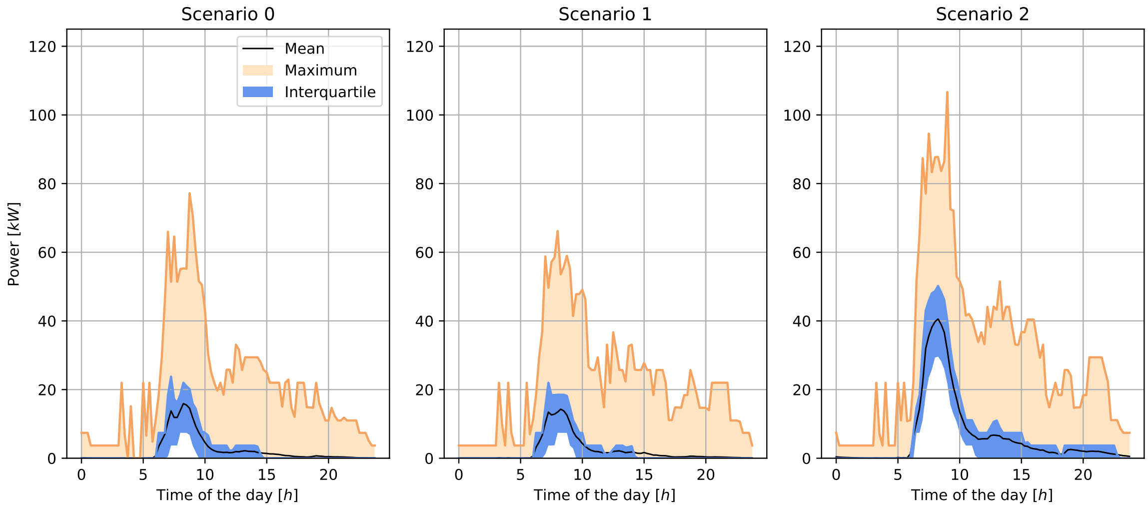

Figure 7: Simulation of uncoordinated charging for the three scenarios.

Figure 7 shows a multitude of interesting observations to discuss. A first common observation for all scenarios is the power peaks during the morning hours. This is because most of the charging sessions start in the morning (as seen in Table 1) using the current uncoordinated charging method. A second observation is the similarity in power dynamics between scenario 0 and scenario 1. This observation is another way to validate the methodology proposed in this paper.

Finally, in scenario 2, clusters 0, 2, 4, 5 and 7, which correspond to morning charging sessions, show the increase in the morning peak from 14.3 kW to 40.5 kW. This represents an increase of 283 %. Maximum peaks that happened exceed 100 kW, which would probably not be supported by the electric system. In this particular case, the electric system could be upgraded to accept higher powers. However, from Table 1, the drivers from the clusters usually require a low amount of energy and stay a long time parked. This means that they have a high charging flexibility and could be good candidates for smart charging.

4 Conclusion

In this paper, an EV charging sessions generator is presented. It enables the creation of charging sessions data based on historical data of a specific charging location. The historical data have been analyzed to group different type of EV drivers together. For each group, specific sets of statistical parameters are extracted, which are then used by the generator. The full methodology is applied on a use case of a hospital which plans to expand its electric vehicle fleet. The results are presented in two parts.

A first part is dedicated on the clustering of EV charging sessions from historical data. The different types of EV drivers are presented with some important characteristics. The results show the big differences in behavior between the EV drivers and the importance of grouping such drivers. A second part focuses on the actual generation of EV charging sessions data. The generator is validated by comparing the historical data set with a newly generated session according to populated clusters. One such scenario is defined and analyzed by ways of by simulating uncoordinated charging for the generated charging sessions. The results indicate the strong impact on power and energy demand when adding new EV drivers to the population. In the analyzed scenario, it showed the need for grid reinforcement or smart charging technologies to avoid overloading and peak demands due to increase of charging session of specific EV driver types. The good results of the validation process demonstrate the potential of this generator to simulate new scenarios while the scenario analysis demonstrates its usefulness to analyse future EV transition scenarios.

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Presenter Biography

Ir. **Gilles Van Kriekinge** obtained his Master's Degree in Electromechanical engineering at the Université Libre de Bruxelles (ULB) in 2019, with a specialization in energy. His master thesis is about a techno-economic assessment of the integration of solar energy, storage system and vehicle-to-grid technology in a microgrid. He is currently a PhD candidate at the Vrije Universiteit Brussel (VUB) and is working on the project "Optimized bi-directional & smart vehicle charging in local energy systems (OPTIBIDS)".

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Dr. Prof. **Thierry Coosemans** obtained his PhD in Engineering Sciences from Ghent University in 2006. After several years in the industry, he became a member of the MOBI research team at the VUB, where he works now as the co-director of the EVERGI team on sustainable energy communities. He is currently involved in the Green Energy Park Zellik, and in the VLAIO-funded projects ROLECS, MAMUET and OPTIBIDS. On a European level, Thierry was and is involved in the H2020 and FP7 projects SafeDrive, OPERA4FEV, SuperLIB, Smart EV-VC, Batteries20202, GO4SEM, FIVEVB, ELIPTIC, MOBILITY4EU, FUTURE-RADAR, OBELICS, REDIFUEL, CE-VOLVER, BD4OPEM, INTERCONNECT and RENAISSANCE, which he coordinates. His main research interests are the development of CO2-neutral Sustainable Local Energy Systems and the performances of electric-vehicle fleets under real-life conditions, including in a V2G perspective. Thierry is an active member the Bridge Initiative and Flux50.

Prof. Dr. **Maarten Messagie** is the co-director of the research group EVERGi at the Vrije Universiteit Brussel. The interdisciplinary research group EVERGi combines knowledge from engineering, environmental, social, economic and data science with 30 dedicated researchers to develop new digital innovations for sustainable multi-vector systems (electricity, water, heat, cooling, data, mobility, hydrogen, efuels, . . .). EVERGi develops and operates a co-creation living lab, demonstrating real-life applications of crucial elements in the energy transition including for instance the integration of electric (and automated) vehicles, with local energy communities and thermal grids.