Exploring Electric Vehicles Energy Flexibility in Buildings

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Abstract. The large-scale integration of electric vehicles presents a challenge for the management of electrical distribution grids. These vehicles differ from conventional ones mainly in the need for charging. Due to user behavior, most vehicles charge simultaneously, leading to possible negative impacts on the electrical distribution grid. The digitalization of grid management can support solutions designed to mitigate those impacts through smart charging strategies. Even considering user comfort, charging of electric vehicles can be controlled thus providing energy flexibility to the building. This energy flexibility can be exploited to achieve different objectives, such as reducing end-user electricity costs while minimizing charging peak load. This paper addresses the impacts of large-scale integration of electric vehicles on a building's electricity consumption and the development of a charging management strategy to mitigate possible negative impacts. The study considers a building and a car park located in NOVA School of Science and Technology, Portugal. Multiple combinations of possible charging power values, electric vehicle penetration ratios and parking times are considered.

Keywords: Electric Vehicles, Energy Flexibility, Demand Side Management, Smart Charging

1 Introduction

In recent years, the relevance of Electric Vehicles (EVs) has grown significantly with integration levels increasing exponentially [1]. This is as a result of the incentives provided by several countries in this sector [2]. In addition to these incentives, the growing awareness of the population regarding climate change contributes to the increased uptake of electric vehicles as they are associated with lower greenhouse gas emissions over their life cycle compared to conventional fossil fuel vehicles [3], [4]. These vehicles are expected to play a larger role on our lives in the future with the European Union expecting at least 40 million EVs on the road in Europe by 2030 [5]. However, EVs do not refuel as their fossil-fuelled counterparts as their batteries need to be charged. This charging can introduce several challenges to the management of the electricity distribution grid, such as voltage drop or high peak loads. These effects are aggravated when uncoordinated charging is observed [6].

By exploring the energy flexibility provided by EVs these negative effects can be mitigated. In this case, energy flexibility is defined as the amount of power demand that needs to be modified at each instant in order to achieve the desired load profile, while taking into account the specific objectives to be achieved and the user's comfort needs [7], [8] [9]. In order to utilize the energy flexibility made available by an electric vehicle within a system, the charging process must be coordinated. This coordination can be accomplished through different control and communication strategies. Typically, two main approaches are considered, namely centralized and distributed. Centralized approaches have greater reliability in controlling charging and can be easily integrated into existing power system control paradigms. However, these strategies require a greater amount of information and are most often not as scalable as distributed strategies.

Distributed strategies require more information exchange, but the decision problem is confined to an electric vehicle [10]. Distributed strategies can allow users to more easily interfere in the decision process [11], [12]. Some coordination strategies lie in a middle ground between centralized and distributed coordination, since they can incorporate centralized control, but limit the size of the control problem to defined areas of the system. This approach split the optimization problem into a set of interconnected local optimizations. Under this context, machine learning and artificial intelligence provide new tools to implement optimization strategies [13]–[15].

These optimizations can have different goals with peak power reduction [16], cost reduction [17] and charging capacity optimization [12], [18] being the most common ones [19]. In this study, peak power reduction is the main impact under analysis. As such, the presented results focus on this effect, but other impacts are considered as well.

2 Methodology

This section describes the methodology used to assess the impacts of EV integration on a specific building's electricity consumption and the EV charging management strategy that can be used to mitigate possible negative impacts.

2.1 Impact Assessment

This methodology aims to simulate the charging of EVs and evaluate the impacts of the charging process on a specific building's electricity consumption. In this case it is considered that the building under analysis has an associated parking lot where the users park their cars and charging is allowed. Considering the car parking facility occupancy data, the building's electricity consumption, the model of the EV and a dataset to model the mobility it is possible to determine the vehicles charging patterns and impacts.

The methodology can be summarized with four main steps. Firstly, it is necessary to determine when the EV arrives at the parking lot (the parking occupancy data is used in this step). This process starts by defining the number of EVs entering the park and the respective entering instant. This step is carried out by the $EV_{entries}$ process, which receives through Ent_{park} all the entry times of vehicles in the park and through $\%_{pen}$ the desired percentage of electric vehicles. Considering these inputs, the process randomly selects n entry times corresponding to EVs where n is defined by Equation 2.1. The value n is approximated since the EVs selection is random. All other entry values are considered to be from conventional fossil fuel vehicles without the need for charging.

$$\mathrm{n} \approx \%_{\mathrm{Pen}} * \mathrm{Length}(\mathrm{Ent}_{\mathrm{Park}}) \tag{2.1}$$

Secondly, the State of Charge (*SoC*) upon arrival is necessary. In a real-world scenario this information can be provided by the user or by the EV but in this case it is determined through the vehicle's specific consumption and distance traveled. The distance traveled is determined using the mobility dataset. The distances are generated by $Distances_{EV}$ and are based on the data contained in $Mobility_{Data}$. This allows for different user mobility patterns to be considered. The process $Generate_{EV}$ generates the structures EV_{Gen} that define the electric vehicles to be considered. The possible models are provided by the input $Models_{EV}$ which contains the vehicle's maximum battery capacity EV_{Bat}, the energy consumption per km EV_{Cons}, the compatible charging powers P_a and the proportion of each vehicle in the set of EVs. It is considered that the distance travelled is the total distance since the vehicle's last full charging cycle thus, the *SoC* on the moment the EV enters the park is given by Equation 2.2.

With these values it is possible to determine the EV charging load profile EV_{Load}. This is done through Equation 2.3 and Equation 2.4. Equation 2.3 provides the charging duration for each vehicle assuming that it charges at a constant power P_c until it reaches full charge. The diagram is constructed assuming that there is no consumption before the vehicle enters the park at instant t_i. Charging is considered to start at the moment the vehicle is connected to the charger (for simplicity this is assumed to be the same instant the vehicle enters the park t_i). In order to simplify the methodology, consumption is assumed to be constant and equal to P_c from the moment of start to the end of charging. Charging ends when the t_c duration is exceeded, where t_c is the required charging duration to reach maximum charge. Once charging is completed, the vehicle can remain in the park indefinitely, but there is no more consumption, thus returning the power to zero until the vehicle leaves the park.

$$\mathrm{SOC} = 1 - \frac{\mathrm{EV_{Dist}} * \mathrm{EV_{Cons}}}{\mathrm{EV_{Bat}}} \tag{2.2}$$

$$\mathrm{t_c} = \frac{(1 - \mathrm{SoC}) * \mathrm{EV_{Bat}}}{\mathrm{P_c}} \tag{2.3}$$

$$\mathrm{EV_{Load}}(\mathrm{t}) = \begin{cases} 0, & \mathrm{t} < \mathrm{t_i} \\ \mathrm{P_c}, & \mathrm{t_i} \le \mathrm{t} \le \mathrm{t_i} + \mathrm{t_c} \\ 0, & \mathrm{t} > \mathrm{t_i} + \mathrm{t_c} \end{cases} \tag{2.4}$$

Then, the load profile of the EV must be added to the building's profile ($Building_{Load}$). This needs to be repeated for all vehicles considered in the simulation, resulting in the total load the building has to satisfy (i.e., building demand plus all charging processes) ($Total_{Load}$). Lastly, the resulting profile can be analyzed, and the impacts of the EV charging assessed.

The process $Extract_{Features}$, as the name indicates, extracts several features of the load diagram. This process can receive any load diagram but, in this case, $Total_{Load}$ is used. This process analyses the load diagram and extracts features such as peak-power P_{max}, average power P_{avg} and total consumption C_{total}. This analysis may have time horizons equal to or lower than the load diagram under analysis. For example, the diagram under analysis may have a one-week horizon and only one day of that week be analyzed. This process can also accept another load and compare both. In this case, the building load without vehicle charging is also received by the process. This process not only returns the values of the selected indicators but also the growth factor of each of these against the load diagram without charging. It is also possible to analyze costs with this process if the hourly rate of the building under review is available. Figure 1 presents a diagram for the described methodology, considering the processes involved and the input/outputs datasets.

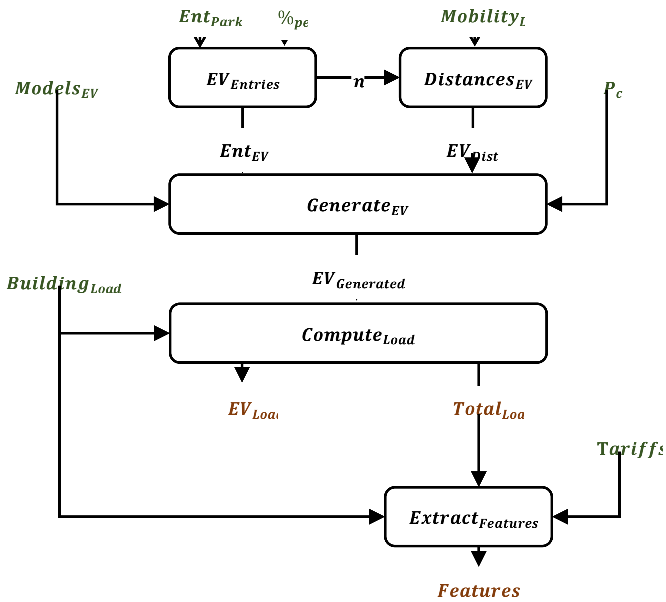

Fig 1 - Block diagram of the impact assessment methodology. Inputs are highlighted in green, outputs in red.

2.2 Charging Management

The typical charging process for Electric vehicles is: (i) Connect to the charger and start the charging process; (ii) Charge for a specified period; (iii) Stay idle until the user arrives. Since the charging duration is usually smaller than the time the vehicle remains parked is possible to offer energy flexibility to the building the charger is connected to. In order to utilize the energy flexibility provided by electric vehicles, a charging management strategy is presented here. The goal of this management strategy is to determine the optimal charging start instant for a vehicle entering the park. In the moment the vehicle enters the park the optimum instant for the charging start, t_τ, is calculated. The vehicle will then remain idle and only start charging at that moment.

Considering the previous methodology, the charging management has its starting point in the structure $EV_{Generated}$. This structure represents the vehicle at the moment of arrival, it contains the time of the entry of the vehicle t_i, as well as its initial *SoC*, charging power P_c and car model description. The departure time of the vehicle, t_o, is the sum of the arrival time with the considered permanence time.

Similar to the previous methodology, this data is used to calculate the vehicle's charging duration through Equation 2.3. If the charging duration is greater than or equal to the vehicle's permanence, the charging in question is assumed to be unmodifiable and the base load profile for this vehicle is considered (i.e., the vehicle maintains the charging start time as the moment of entry into the park). This represents a scenario where there is no energy flexibility. On the other hand, if the vehicle charging can be modified then an algorithm is used to find the best instant to start the charging process.

The optimization function also receives the building's consumption forecast for the period the vehicle will remain parked. This forecast includes the building load forecast and the charging profiles of all vehicles that have previously entered the park. Taking into account the instant of arrival t_i , instant of departure t_o and the charging duration t_c it computes through Equation 2.5 the maximum delay value in which it is still possible to reach the desired *SoC* at the end of the charging process, t_l.

$$t_l = t_o - t_i - t_c \tag{2.5}$$

$$\mathrm{EV_{Load}}(\mathrm{t}) = \begin{cases} 0, & \mathrm{t} < \mathrm{t_i} + t_s \\ \mathrm{P_c}, & \mathrm{t_i} + \mathrm{t_s} \leq \mathrm{t} \leq \mathrm{t_i} + \mathrm{t_s} + \mathrm{t_c} \\ 0, & \mathrm{t} > \mathrm{t_i} + \mathrm{t_s} + \mathrm{t_c} \end{cases} \tag{2.6}$$

In the moment the vehicle enters the park, the load diagram is defined. The main difference in this case is that the load diagram will be shifted by t_s intervals. For each delay value t_s between 1 and t_l, a different charging load diagram is calculated through Equation 2.6 and added to the building load forecast. A function is then used to calculate a cost value for each delay value and the optimization function chooses the delay value that has the lowest cost. The possible delay values start at 1 timestep since the optimization algorithm is not instantaneous. This procedure is repeated each time a new electric vehicle enters the park.

In this case, the cost function was considered to be the maximum power value within the vehicle's parking period. As such, the optimization function will choose the delay value where the peak power value is minimal. If multiple values have the same cost as the optimal one the lowest value is chosen. This allows for the vehicle achieve the desired *SoC* sooner giving more freedom to the user. The flowchart describing this charging management strategy is shown in Fig 2.

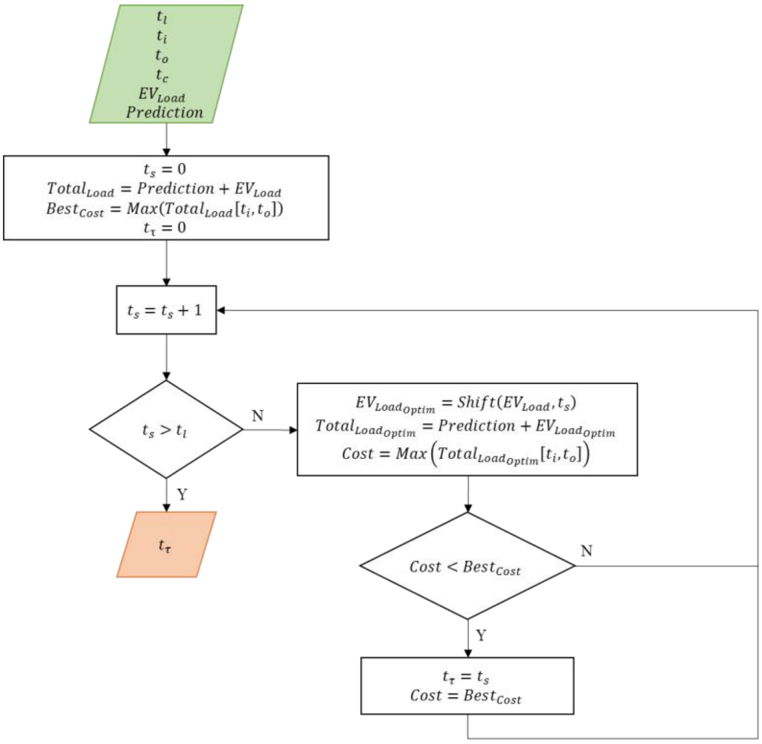

Fig 2 –Vehicle Optimization Function Flowchart

3 Results and Analysis

The results reported in this section were obtained through a case study considering real data associated to a car park and a building located at NOVA School of Science and Technology (FCT NOVA), Portugal. As users of the building are typically students, professors, or staff members, 4, 8 and 12 hours were considered as vehicle parking time. The charging power considered were 3.7, 7.4, 10 and 22 kW as these are the more typical ones, as indicated by the report of the European Energy Agency presented in [20].

3.1 – Case Study Data

The case study presented focuses on the building of the Department of Electrical and Computer Engineering (DEEC). The building load was obtained using a smart meter installed in the building. Its consumption consists mainly of lighting, personal computers, servers and computers installed in the laboratories. Although there are also electric motors and water pumps in the building, these are not regularly used. As this building is mainly used for academic purposes, its load diagram shows higher consumptions on weekdays, as shown in Fig. 3, which presents the building's load profile for a specific week during school time. The building consumption follows a clear pattern. The consumption starts to increase at the early hours of weekdays, around 7:00h, with peak consumption values over 100 kW around 14:00h-15:00h, and then reduces to the lower values in the evening. It is also possible to see a reduction in consumption on Wednesdays, as these are days with a lower number of classes. This causes a reduction in the number of users of the department thus reducing its consumption. In this case, the peak values are usually between 75 and 80 kW. The consumption on the weekends is lower since the number of users is lower and only the most basic loads are active, such as lighting and servers (it fluctuates between 40 kW and 60 kW in these cases).

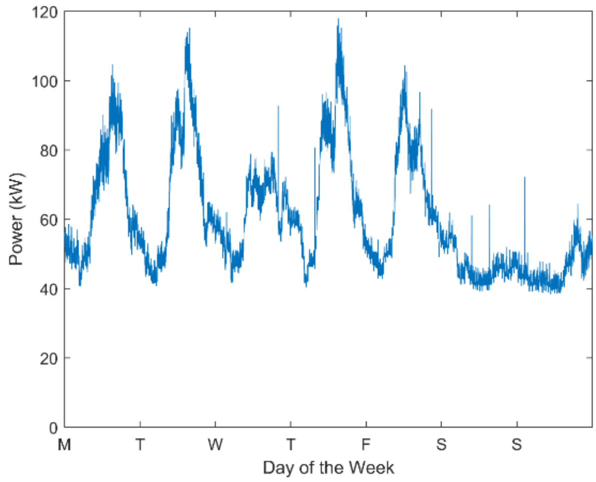

Fig. 3 – DEEC building's load diagram.

As explained before, one input required to simulate the charging of an EV is the vehicle's state of charge. To calculate the state of charge it is necessary to estimate the distance travelled by the EV. The distances are estimated through a probability distribution. The data source used was the study present in [21]. This study monitored 49 drivers who usually circulate in Lisbon area. The drivers were between the ages of 18 and 66 and were of both sexes, allowing for a broad and varied sample. The drivers were monitored from April to September 2010 in monitoring cycles with a duration of one week. These distances were used to create a histogram to determine the distance travelled by each vehicle. As the total number of entries in the parking lot were 1322 it was decided that $Distances_{EV}$ should be able to generate at least 1500 distance values with a similar distribution. The comparison between the histograms of the original values and the values generated for 1500 vehicles is presented in Fig.4.

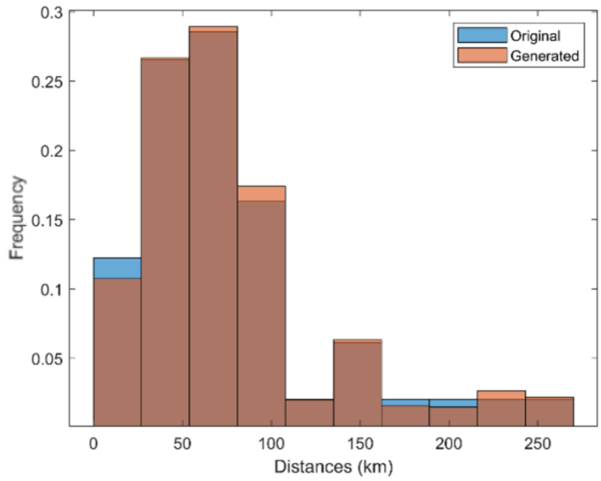

Fig.4 – Comparison between the original and generated histograms.

The entrances of electric vehicles were obtained from data provided by the FCT-NOVA security division. The security division provided the entrance data in the chosen park and the users belonging to DEEC were selected. The data provided correspond to the same week of Figure 3. Fig.5 presents the occupation of the park with stay times of 4, 8 and 12 hours. It is possible to verify a lower occupancy on Wednesdays, which matches with the lower consumption in Fig. 3.

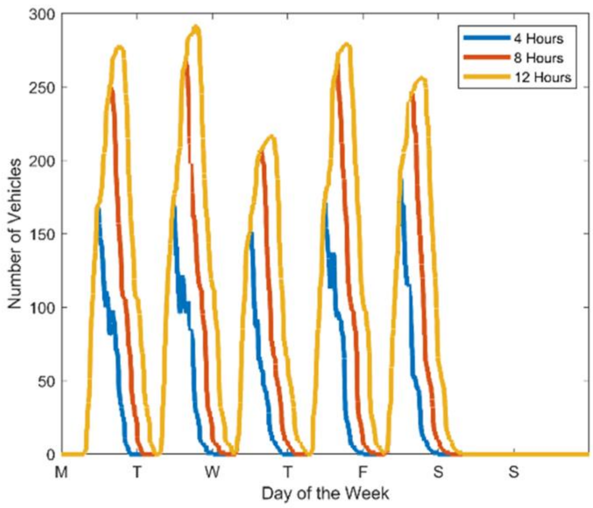

Fig.5 - Parking lot occupation with the considered user stay duration.

Finally, it is necessary to define the vehicle models to consider in the case study. It is necessary to define the specific consumption per km, the capacity of the battery, the possible charging powers compatible with the vehicle and the frequency of respective vehicle in the considered fleet. The models considered are the same as those described in [22], [23] and are presented in Table 1. It is considered that the vehicles are evenly distributed in the fleet, so the $Generate_{EV}$ process randomly chooses one of the four available models.

Table 1 – Vehicle Models considered in the case study

Model	Battery Capacity (kWh)	Specific Consumption (Wh/km)	Allowed Charging Power (kW)
Minivehicle	17,7	146	3,7; 7,4; 10; 22
Medium Vehicle	24,4	170	
Large Vehicle	42,1	185	
Premium Vehicle	59,9	207	

3.2 – Impacts of EV charging

Initially, the impact assessment methodology was applied to 50 scenarios. Each scenario is defined by a charging power and a percentage of penetration. The considered scenarios included all vehicles charging at the same power and also a set of scenarios with random charging powers from among those considered. Penetration percentages range from 10% to 100%, with increments of 10%. The time horizon was a full week with one minute resolution. All scenarios were computed using MATLAB. Fig.6 presents the comparison between the following indicators considered for different EV penetration levels: peak power P_{max} and total consumption C_{total}.

As expected, the total power consumption in all scenarios is independent of the chosen load power and increases with the number of electric vehicles. Total building consumption without EVs charging is 10.07 MWh and with 100% EVs penetration is 27.04 MWh. The impacts of charging are much more evident when considering peak power. Since the case study considered is from a university, users' entrances to the park are usually relatively close. This causes most EVs to charge simultaneously, resulting in a sudden increase in building consumption. This event is clearly visible in Fig.7 where the consumption associated with vehicle charging dwarfs the buildings base consumption. It is possible to see an increase from 49.29 kW at 7:00 to 312.83 kW at 7:30 and to 901.5 kW at 9:30 on Monday when considering a scenario with 100% EV penetration level. This growth is more dramatic in scenarios where the charging power is higher. This rise may be of concern since the power distribution grid may lack the ability to handle such variations. However, in scenarios with lower charging power, although the maximum peak value is lower, the peak duration is longer as vehicles remain charging for longer periods. Considering the energy tariffs for medium voltage power installations available at [24], contracted power costs is 0,0862 €/kW.day. The contracted power costs without EVs is €10.14 per day. If the same rates are applied to the 3.7 kW charging power scenario and 20% penetration this value increases to €18.18. With 100% EV penetration the daily value would be €53,87. As seen in Fig.6, the 3.7 kW scenario produces the lowest peak power in all scenarios whereas 22 kW scenario produces the highest. This is due to most of the charging periods being simultaneous. If charging was performed with 22 kW instead of 3.7 kW the values for the daily contracted power would be 31,55 € for 20% and € 88,36 for 100% EV penetration. This shows that EVs load management is required not only to reduce peak loads but also the costs associated with contracted power.

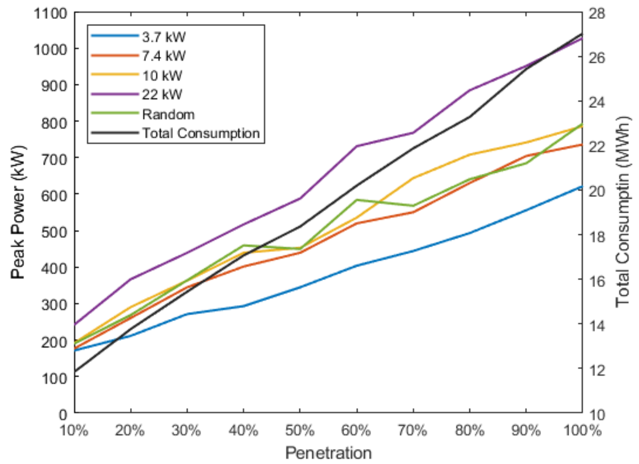

Fig.6 - Peak power and total energy consumption for different charging powers and EV penetration levels.

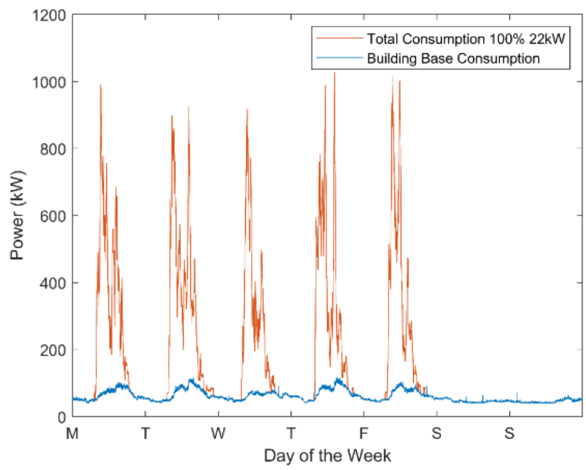

Fig.7 – Building's load diagram with 100% EV penetration and 22kW

3.3 – Benefits of Energy Flexibility Usage

Collected results show that the charging management strategy can decrease building's peak load and associated costs. As can be seen from Fig.8, peak power is reduced by at least 20% when the load management strategy is applied. It is also possible to note that the load profile is significantly smoother. This is due to the optimization function shifting the charging to later periods in an attempt to not increase the peak power. When considering all scenarios, a considerable reduction in peak power is observed as presented by Fig. 9. Although total energy consumption remains the same, the problem of high-power peaks is mitigated by the management strategy. Previously, an increase in the number of EVs produced a significant increase in peak power but now as the charging periods are distributed throughout the day the increase in peak power is not as significant. As an example, with 22 kW as the considered charging power, by increasing the penetration of EVs from 20% to 30%, EV the peak power increased from 366.61 kW to 439.19 kW but in the case of 12-hour coordinated charging, this increase in the number of EVs translates into increasing the peak value from 140.21 kW to 171.74 kW. Even though in both cases the increase is around 20%, the values are significantly lower in the scenario with the management strategy. Even scenarios with higher charging power have peak values very close to those with lower power values. For example, prior to charging management, the 100% penetration scenario with 3.7 kW has a peak of 621.69 kW and with 22 kW has a peak of 1027.30 kW. With load management, these values are reduced to 366.75 kW and 324.23 kW, respectively. The results show that this management strategy presents better results when penetration and charging power are increased. Higher charging power values can produce lower peak values when charging is managed. This is due to lower charging power values resulting in longer charging periods and more simultaneous charging. As the number of vehicles increase the proportion between the consumption of the vehicles and the building also increases and the impact of the optimization is more evident. This presents an opportunity for this management strategy since high-power charging is increasingly available and the number of EV purchases increases yearly.

An important factor to also consider is the parking duration. The longer the stay the better the results. The 12-hour scenario presents the greatest improvement in reducing peak power due to the increased distribution of charging periods. This effect is most evident at higher charging power values as charging durations are shorter. At lower charging powers, the charging duration is increased which can lead to some vehicles still charging simultaneously. However, this distribution can stretch the consumption into later hours. As mentioned above, this management is only possible due to the existence of energy flexibility in the charging of electric vehicles.

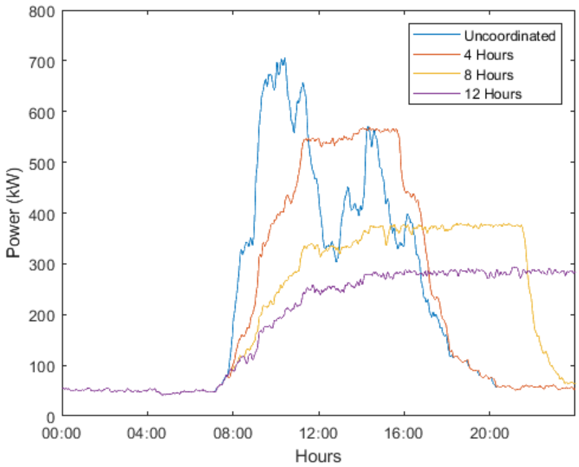

Fig.8 - Comparison between consumption diagram with and without charging management for Monday.

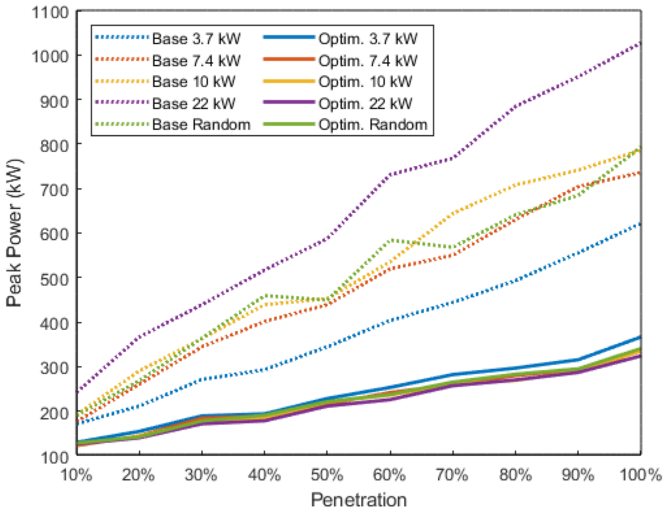

Fig. 9 - Comparison of the peak power in scenarios with and without charging management with 12 hours of user stay time.

4 – Conclusions

The collected results show that some of the main impacts of increased EV penetration in a vehicle fleet are the increase in peak power and total energy consumption. Even though both increase with the number of vehicles, peak power values vary with the chosen charging power while the total consumption does not. The increase in peak power is amplified when the charging power is increased. This shows that the integration of high-power chargers into a building can be detrimental even in low EV penetration scenarios. The uncoordinated charging at 22 kW with 10% and 20% EV penetration represents an increase of 41% and 73% of the peak power, respectively, when compared to the uncoordinated charging with 3.7 kW. Thus, the constant increase in electric vehicle adoption might impose negative impacts on distribution grids operation if only uncoordinated charging is available.

When charging management is applied, improvements in the peak power values for all scenarios are observed. One important result is that peak power values are not related with the chosen charging power. When higher charging powers are considered, such as 10 kW and 22 kW, the peak power value is similar to the ones with lower charging power values. Increasing the parking time also provided better results as expected, with charging periods being spread out. With 8 hours of parking time, the power peak values start to converge and the relation between charging power and peak power value is no longer relevant.

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