POTENTIAL BENEFITS OF SCHEDULING ELECTRIC VEHICLE SESSIONS OVER LIMITING CHARGING POWER

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ABSTRACT

This work addresses the management of charging infrastructure to cope with the problem of congestion in the electric grid by exploiting electric vehicle (EV) flexibility. Benefits of scheduling charging sessions based on user profiles is compared with two traditional methods for limiting charging power: using static a dynamic control signal. The user profile concept is a classification strategy that consists in assigning a label to every EV user, referring to a connection pattern in the daily use of the charging infrastructure. The study analyses pros and cons of these three approaches and highlight the advantages of demand-response programs based on the user profiles. Thus, while limiting the power of charging sessions with a static signal causes a rebound effect, using a dynamic signal requires impacting a high amount of sessions. Scheduling (i.e. postponing) the charging sessions associated to profiles with low-variance provides a higher efficiency of the demand-response program since the same objective (i.e. peak demand reduction to 350 kW) is achieved with a lower number of participating sessions (40% fewer than limiting charging power with dynamic signal).

INTRODUCTION

The electrification of final energy demand that consumes fossil fuels as energy source, such as transportation or heating systems, can lead the distribution grid to critical congestions during peak hours, mostly in low-voltage distribution grids and at substation level [1]. At the same time, the challenge that supposes the introduction of electric vehicle (EV) also provides an opportunity to distribute the storage resources and make use of a strong flexibility potential. The flexibility that an electric vehicle can provide to the electric system is of a special interest for the DSO in order to support congestion management at specific geographic locations [2]. The flexibility of a single vehicle is small, but the aggregated impact of a fleet or the management of large charging infrastructures (e.g. public charging stations) can be significant to participate in flexibility markets through aggregators [3].

Thus, EV flexibility aggregator could be a new market player together with other actors already active in the EV sector, such as parking or fleet owners, Charging Point Operators (CPO) or e-mobility service providers (EMSP) [4]. At the same time, the method to control the EV charging process can be also diverse, for example the charging point (communication Aggregator - CPO), the EV itself (communication Aggregator - Car manufacturer) or the Home Energy Management System (communication Aggregator - HEMS).

The following sections describe and analyze three different approaches to manage the EV load for congestion management from the aggregator point of view: (1) static signals to limit charging power, (2) dynamic signals to limit charging power and (3) dynamic signals to schedule (i.e. postpone) charging sessions.
Section 2 describes the three flexibility strategies and learnings from real pilot projects aiming to highlight the contributions of this paper. Section 3 presents the simulations done for these three smart charging methods. Finally, Section 4 concludes with main results from these simulations.

SMART CHARGING FOR GRID CONGESTION MANAGEMENT

During last years, several pilot projects in Europe have evaluated the local impact of EV charging in the electric network and the methods to avoid grid congestions. One of the most extended methods is the limitation of the power that the charging points can supply with a *static control signal* or power profile. An example of a successful pilot is the Flexpower project in Amsterdam [5], where the phase current of 39 public charging stations (25A nominal) was limited to 20A from 07:00–08:30 and to 6A from 17:00–20:00, but increased to 35A during the rest of the day. In the second phase of the same project, Flexpower 2 [6], the phase current was limited from 18:00 to 21:00 to a maximum of 8A, and the rest of the day to 35A, except during the cloudy days (no PV production), when the current was limited to 25A from 6:30 to 18:00. Another pilot that implemented a static power profile limitation was carried out by the Dutch DSO Enexis [7], using domestic charging points in this case, reducing the charging current from 17:00 to 22:00 to a maximum of 6A.

However, both Dutch pilots experienced some drawbacks on their implementations. The most direct side-effect of constraining the EV load between a peak period is a rebound effect. The energy is shifted from the constrained to the unconstrained time period. Even though a rebound is not a problem during valley hours, it could be significant if not properly controlled. It is necessary to explore the opportunities of reducing rebound peaks, for example by designing more gradual increase in charging speed after the off-peak limit [5] or applying dynamic control with feedback from real-time monitoring.

With this objective, the Enexis pilot [7] also proposed a *dynamic control signal* to reduce the charging power according to an aggregator signal. In this scenario, the rebound effect is highly avoided since the increase of demand is continuously corrected thanks to real-time measures. This flexibility framework where the charging power of the sessions is modified according to the signals of an aggregator has been also tested by several Horizon 2020 projects such as Interflex [8] and INVADE [9]. In both projects, the reduction of power depends on the free capacity of the grid, considering also the local PV power and households' demand. In the INVADE pilot, all charging points were treated equally, so once the dynamic power profile is adjusted, it is used for all active sessions. This method, even though it is directly deployable, is low-efficient since it uses a lot of resources (i.e. charging sessions) that have a cost, reaching a value of 77% of exploited sessions during a month with high domestic consumption [9]. Moreover, even though the method is equally applied to all sessions it does not mean it is an equalitarian treatment. If the EV user can not choose whether to participate or not in the smart charging program, the impact of reducing the charging power is higher for a user that is only connected for 3 hours than another that will remain connected the whole night. In contrast, the users participating in the Interflex project could choose whether to participate or not, receiving a financial reward in exchange for their flexibility. At the same time though, extrapolating this method at city level like the INVADE approach could make the business model more difficult since the exploitation costs would be too high, given that if the reward is not relevant for users they wouldn't provide their flexibility.

Therefore, it is necessary to use a dynamic control signal to avoid a rebound effect during off-peak hours, and exploiting only the most flexible sessions to ensure (1) a high quality of service to all users (i.e. both long and short sessions should have time to charge the EV) and (2) a high efficiency of the demand-response program (i.e. lower exploitation costs). However, selecting only some of the available sessions for the demand-response program supposes a risk for the aggregator of not achieving the flexibility offer or exceeding the grid capacity. The aggregator should know beforehand which are the EV users with the highest flexibility potential. In order to optimize these issues, this paper proposes a smart charging method that takes into account the differences between user profiles and uses this extra knowledge to perform an efficient and reliable scheduling of EV charging sessions.

COMPARATIVE ANALYSIS OF SMART CHARGING STRATEGIES

In this section, three different strategies to manage the aggregated EV load are compared:

1. Limiting charging power according to a static control signal
2. Limiting charging power according to a dynamic control signal
3. Scheduling charging sessions based on user profiles and dynamic control signal

A real data set from the municipality of Arnhem, in The Netherlands, consisting on 253 charging sessions in 133 charging points of the public charging infrastructure (4rth February of 2020), has been used to illustrate the impact of smart charging according to the mentioned scenarios. The original demand profile of these sessions is shown in Figure 1.

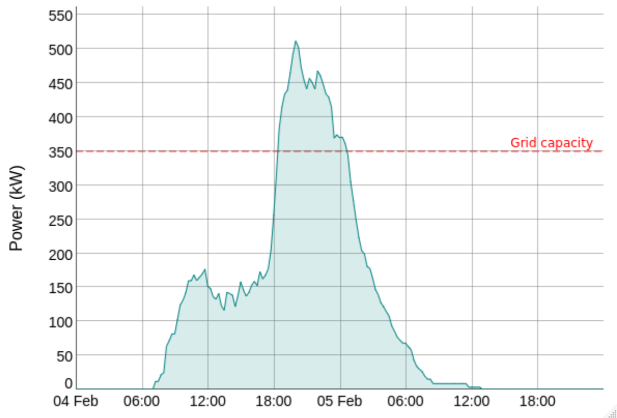

Figure 1. Original EV demand in Arnhem during the 4/02/2020

For the experiment, a maximum grid capacity of 350 kW has been assumed. This evidences a congestion during the peak hour (18-22h). Below, the implementation of the different smart charging strategies with the same real data containing the sessions are simulated.

Limiting charging power with static signal

In cases where a communication infrastructure between the DSO and the CPO or the implementation of a flexible market is not possible, limiting the maximum phase current of charging points is a direct practice to avoid congestion during peak hours. Following the implementations done in [5] and [7], this simulation has considered a charging point limitation of 6A per phase from 18:00 to 22:00, shown in Figure 2.

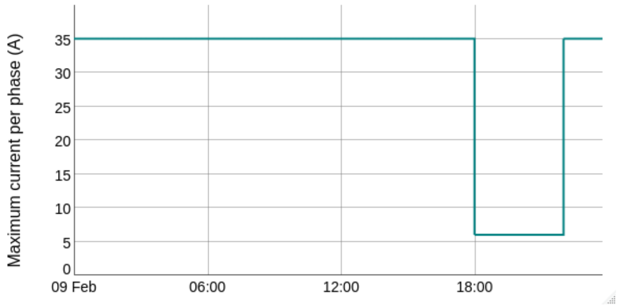

Figure 2. Static control signal for every charging point

Since some charging points need a minimal current of 6A, the lower limit of a control signal was therefore fixed to this value to prevent charging sessions from stopping [10]. To simulate the implementation of a static control signal, the charging sessions have been assumed to charge with single phase, given that it is the predominant category in the current Dutch EV market [5]. Figure 3 shows the implementation of this method for the real data set of charging sessions in Arnhem. Even though the maximum demand from 18:00-22:00 has been reduced to 270 kW, a rebound effect is visible resulting in a peak demand of 495 kW after 22h, only a 3% lower than the original scenario.

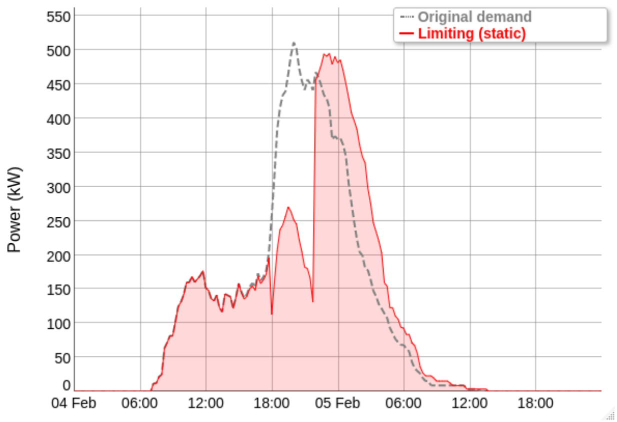

Figure 3. Static control signal for limiting charging power

Limiting charging power with dynamic signal

The use of a dynamic power profile giving the maximum charging power allowed at a timeslot assumes that the aggregator communicates in real-time with the DSO to get the maximum power allowed at every timeslot and therefore calculates the power reduction in case of congestion. Inspired in [9], the algorithm designed for this scenario does the following sequence: when the grid capacity is surpassed, the total power to be reduced is divided by the number of sessions charging at this timeslot and the corresponding kW are cut down for every session. The implementation of this method is shown in Figure 4. Since the simulation assumes a real-time communication between the EV demand measurements and the power curtailing mechanism, the EV load is completely shaved to the value of 350 kW (i.e. grid capacity threshold), without any rebound.

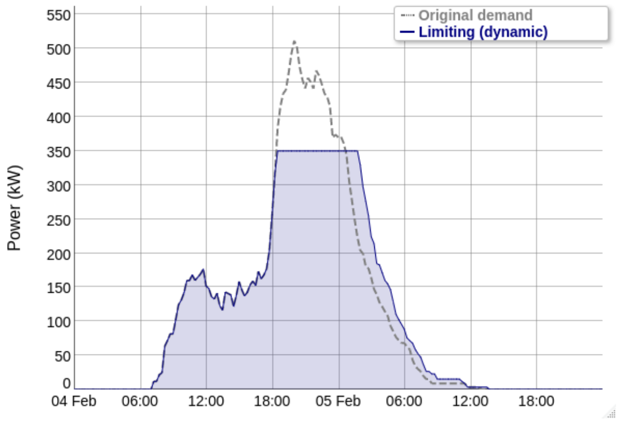

Figure 4. Dynamic control signals for limiting charging power

Scheduling charging sessions based on user profiles and dynamic signal

The smart charging method in this case does not consist on reducing the charging power of the EV sessions but postponing the entire session to the next timeslot. This postponing process is repeated for every session that starts in any timeslot with an aggregated demand higher than the grid capacity. Nevertheless, the key-point of the method presented in this paper is that not all sessions are postponed but just the ones belonging to certain user profiles with a proper flexibility potential.

A user profile is understood as a pattern in the connection times of EV users. This concept is deeply described in the previous research published in [11], which this paper wants to complement and provide further results. These user profiles are obtained after clustering a dataset of sessions with bivariate Gaussian Mixture Models (GMM), using the connection start time (from 0 to 24) and the connection duration (in hours) as clustering variables. The different clusters are grouped into generic user profiles (e.g. Worktime, Visit, Dinner, etc.) based on their centroid but also on their variability (i.e. dispersion of the points belonging to the cluster).

The Arnhem's data set used in this paper was already analyzed in [11] to discover generic EV user profiles for aggregated flexibility planning. Concretely, seven different user profiles were found, which can be classified into 3 different groups according to their variability:

- Low-variance in both connection start time and duration: Worktime, Dinner, Commuters and Pillow
- High-variance in connection start time but low-variance on connection duration: Shortstay
- High-variance in both connection start time and duration: Home, Visit

To visualize the EV demand of every user profile in Arnhem, Figure 5 shows their real demand during the day in the scope of this paper. The visible combination of bell-curves in their power profiles are the result of the GMM clustering. Aggregation of these profiles will result in the total demand curve presented in Figure 1.

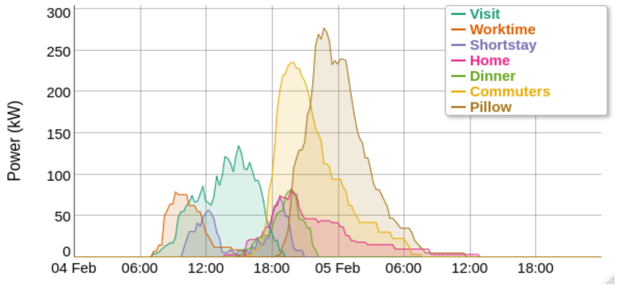

Figure 5. Original EV demand by user profile

Thus, in the scenario raised in this section, the aggregator pre-classifies the existing EV users (for example through unique RFID cards, or and Id associated with the vehicle) between generic user profiles, and then activates the flexibility of the proper user profiles according to the optimization goal. In this case, the objective is to reduce the evening peak, which is caused by the user profiles Dinner, Shortstay, Home, Commuters and Pillow. From these profiles, Shortstay and Dinner are short sessions that can't provide flexibility without being affected. Home users are too variable in both Connection start time and Connection duration to be confident about their flexibility. Commuters are a very reliable user profile that has a big flexibility potential for peak shaving. Pillow sessions start later than Commuters but stay connected during all night, so they also have flexibility potential for peak shaving.

Therefore, in this scenario the aggregator has chosen to postpone sessions belonging to Commuters and Pillow users to reduce the EV demand below the grid capacity threshold that the DSO requested, which in this case is a maximum power of 350 kW. The resulting simulation is shown in Figure 6, resulting in similar shape as the solution provided by the dynamic signal approach but with a significant reduction of users involved.

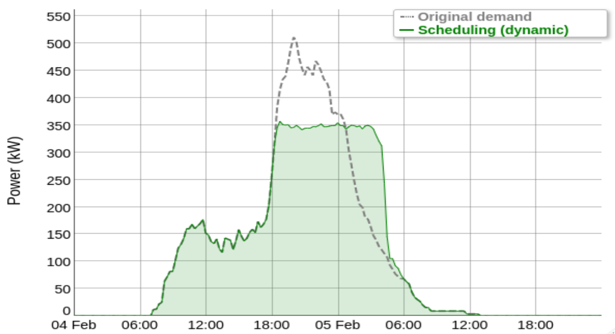

Figure 6. Scheduling based on user profiles

RESULTS AND CONCLUSIONS

In this work, a scheduling methodology based on EV user profiles is presented to deal with the main drawbacks of limiting charging power to manage grid congestion. Common drawbacks and learnings from existing project pilot projects are summarized below:

- *Rebound effect*: limiting charging power with a static control signal results in a higher peak right-after the limitation stops. This side-effect shouldn't be a problem during demand valley hours but it must be controlled.
- *Impact on users*: limiting charging power of all connected EVs may be a problem for users connecting for a short time if they don't have time to charge enough energy with a low-power rate. This could happen with both static and dynamic signals if the charging limitation is applied to all charging EVs.
- *High exploitation costs*: if the aggregator pays a financial reward the users participating in the demand response program, the price must be relevant for EV users. Limiting charging power of all connected EVs may result in too high exploitation costs.
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The potential benefits of scheduling (i.e. postponing) charging sessions in terms of rebound, impact and efficiency in comparison to limiting charging power have been evidenced in this work. The proposed method has the following main features:

- Classification of EV users between generic user profiles based on connection times. From these user profiles the aggregator will select the most reliable (i.e. low-variability Gaussian models) user profiles that could provide flexibility for a certain objective (e.g. peak shaving). Only sessions belonging to the selected user profiles will participate to the demand-response program, decreasing the exploitation costs and the uncertainty of the flexibility.
- A real-time dynamic control signal determines the available grid capacity at every time slot. If the EV demand is expected to surpass the grid capacity, then sessions belonging to selected user profiles will be postponed to the following time slot until reaching the setpoint.

In order to justify the methodology, three different charging strategies have been compared using real charging sessions. The main numeric results and the corresponding conclusions are listed below:

- The final peak demand has been reduced a 32% with strategies using dynamic signals, while the static signal scenario resulted in a rebound effect, supposing an overall demand peak 3% lower than the original value.
- The number of exploited sessions is highly reduced using a scheduling based on user profiles (24% of

sessions) rather than limiting charging power with both static (40% of sessions) and dynamic (64% of sessions) signals. It is logical given that the scheduling method exploits only the most reliable sessions.

- The direct side-effect of exploiting all connected EVs is the impact on users' energy charged. However, for this case study the affectation is minimum. Using a static control signal, a 7% of sessions charged less than 90% of the energy originally required, while only 4% charged less than 75%. Using a dynamic control signal a 9% of users charged less than 90% of energy while 3% charged less than 75%.
- Scheduling charging sessions has no affectation on users' energy charged, since the algorithm only postpones a charging session if it has enough flexibility. This assumption requires a high knowledge on the user behavior and, for this reason, only low-variance user profiles are used.
- Using EV user profiles to select which sessions to postpone has resulted in a more efficient implementation at the same time than the grid capacity has not been exceeded.

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REFERENCES

[1] V. Slednev, P. Jochem, and W. Fichtner, 2021, "Impacts of electric vehicles on the European high and extra high voltage power grid," *J. Ind. Ecol*.

[2] M. Van Amstel, 2018, "Flexibility system design for electric vehicles. Performing congestion management for the DSO."

[3] H. P. Khomami, R. Fonteijn, and D. Geelen, 2020 "Flexibility market design for congestion management in smart distribution grids: The dutch demonstration of the interflex project," *IEEE PES Innov. Smart Grid Technol. Conf. Eur.*, vol. 2020-October, pp. 1191–1195.

[4] USEF and Jedlix, 2020, "Case study: practical deployment of electric vehicle flexibility".

[5] P. C. Bons, A. Buatois, G. Ligthart, F. Geerts, N. Piersma, and R. van den Hoed, 2020, "Impact of Smart Charging for Consumers in a Real World Pilot," *World Electr. Veh. J. 2020, Vol. 11, Page 21*, vol. 11, no. 1, p. 21.

[6] SEEV4-City Interreg project, 2020, "Final report Amsterdam Flexpower Operational Pilot: A detailed analysis of the effects of applying a static smart charging profile for public charging infrastructure".

[7] M. Berende, N. Refa, P. van Bokhoven, and L. Gardien, 2020, "Network peak load reduction by home charge management of electric vehicles" *IET Conf. Publ.*, vol. 2020, no. CP767, pp. 337–340.

[8] D. Geelen, N. Refa, and R. Spiering, 2019, "Smart Charging Electic Vehicles Based on a Flexibility Market," *CIRED 2019*, vol. 1, no. June, pp. 3–6.

[9] M. Zweistra, S. Janssen, and F. Geerts, 2020, "Large Scale Smart Charging of Electric Vehicles in Practice," *Energies 2020, Vol. 13, Page 298*, vol. 13, no. 2, p. 298.

[10] P. Van Bokhoven *et al.*, 2020, "Charge management of electric vehicles at home: Testing smart charging with a home energy management system".

[11] M. Cañigueral and J. Meléndez, 2021, "Electric vehicle user profiles for aggregated flexibility planning" *2021 IEEE PES Innov. Smart Grid Technol. Eur. (ISGT Eur.*, pp. 1–5.