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Integrating Guarantees and Veto-Buttons into the Charging of Electric Vehicles at Office Buildings

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Abstract—**The electricity demand by electric vehicles (EVs) is rapidly increasing and will lead to violations of grid capacity constraints if supplied in an uncontrolled manner. However, introducing controlled charging often makes EV users feel anxious. To increase the transparency of coordinated charging, we propose a framework of charging guarantees and veto-buttons that provides users with a sense of control. Here, veto-buttons allow users to opt for fast charging instead of controlled charging. We demonstrate the effectiveness of the features for an office parking lot use case, modelled based on a large real-world EV charging parking lot in Utrecht, the Netherlands. Using data from real charging sessions and the work-home commute distance surveyed among EV-driving employees frequenting that parking lot, we demonstrate the effect of the features on the aggregated power profile and its compliance with local grid capacity constraints. In particular, we show that when simulating 400 EVs behind a 1.3 MW power connection, controlling around 60% of the EV population based on their commute-distance information suffices to operate within power limits, even if the remaining 40% of the EVs opt for fast charging of their full electricity requirement using veto-buttons.**

***Index Terms*—electric vehicle, system integration, user experience, smart grid**

I. INTRODUCTION

The transition to electric vehicles (EVs) is driven by sustainability considerations. However, the subsequent increase in electricity demand by EVs is coming with challenges and without proper control will lead to violations of grid capacity constraints [1] and thereby to potential outages. A possible countermeasure for this are coordinated charging strategies which can help mitigate local power peaks if provided with sufficient information on e.g., the EVs' individual dwell time and energy demands. Yet, in practice, that information is usually not available [2]. A possible solution may be to request direct user input per charging session, where users are the EV drivers that want to charge their vehicle. However, studies have shown that direct user input is often inaccurate and that it is challenging to ensure long-term user participation [3]. Furthermore, EV users often feel anxious when exposed to smart charging [4]. In order for such strategies to be effective and not fail due to lacking user participation, transparency is crucial to build trust in smart charging in public spaces like office parking lots [5].

In this research, we propose a generic framework with two features that integrate users into coordinated charging processes by making charging objectives more transparent, support edge cases, and provide the user with a sense of control. Firstly, we propose charging guarantees that are simplistic, yet effective, based on information that is invariant over multiple charging sessions. Secondly, we suggest the implementation of a veto-button that allows users to opt-out of the default coordinated charging and do fast charging instead.

To get more insights in the proposed measures, we study a use case inspired by a real-world parking lot at an office location in Utrecht, the Netherlands [6]. We propose to guarantee that sufficient electricity for the work-home commute is supplied to the EV within a specific time period (six hours in our use case). We integrate these constraints into a planning approach for scheduling the charging of EVs. Using real-world charging sessions collected at the office parking lot, and the work-home commute distance surveyed among EV-driving employees frequenting that parking lot, we demonstrate the effect on the aggregated power profile of the parking lot and its compliance with local grid capacity constraints.

In literature, various use cases that promote transparency and control from a user perspective are discussed already. For example, there are studies available where direct user input was collected and dedicated charging schedules were communicated to the users at the beginning of a charging session to increase transparency [7] [8]. However, this requires a suitable communication channel, e.g., a mobile application. Such applications have also been developed to research user acceptance of vehicle-to-grid [9], or to provide users with the operational control over the applied charging modes [10]. The study in [11] introduced high-priority request buttons. Here, upon a high-priority request, the charging would be controlled with a higher charging priority than other EVs. In addition, the study ran large-scale trials in residential areas showing that initially 4% of all requests used the high-priority option, which stabilized later at 2.5%. The mentioned trials are restricted to residential areas and their results do not necessarily translate to other use cases. These examples show that there may be big differences between EV charging use cases depending on

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e.g., the physical setting, scale and data availability. This asks for tailoring the user integration per case, making the generic and adaptable framework presented in this paper a valuable addition to existing methods.

The remainder of the paper is structured as follows. Section II describes the conceptual framework of charging guarantees and of the veto-button, the office building use case and corresponding data, and the method applied in the numerical experiments. Based on this, we present numerical results in Section III. Section IV provides a list of practical add-ons and considerations for adapting the framework to other use cases. Finally, we discuss the guarantee and veto-button framework in the light of the results in Section V and round up with a conclusion and future work in Section VI.

II. METHODS

In the following, we describe the conceptual framework, the data sets collected for and used in this study, as well as the modelling assumptions made in the numerical experiments.

A. Conceptual framework

The presented framework highlights two features that can be integrated into coordinated EV charging methodologies to promote user integration and bridge information gaps.

Firstly, we propose *charging guarantees* as default charging mode in the planning and communication with users. As pointed out, (online) scheduling algorithms for EV charging use (a proxy for) information on the energy requirements and dwell times of individual EVs. Charging guarantees therefore may be defined by

- a minimum amount of electricity to be delivered and
- a deadline by which this minimum amount has to be delivered.

Secondly, we propose the introduction of *veto-buttons* that allow users to actively opt-out and choose for fast-charging upon starting their charging session instead.

B. Numerical experiments and use case

We integrate the presented generic framework into an existing methodology for an office building use case with 400 EVs. Here, we present the control strategy, integration of the charging guarantee and of the veto-button, real-world data and model assumptions.

The control strategy we use is event-based profile steering [12] with as objective maximizing the flatness of the aggregated power profile. Event-based profile steering is a two-stage optimization heuristic that operates as follows. Firstly, the method requires an aggregated target profile $\vec{p}$. For convenience, we choose the flattest feasible profile which we find assuming that prior to the planning horizon all information on individual arrival times, departure times, electricity requirements and whether or not an EV is controlled is known. In doing so, we may use the target profile $\vec{p}$ as an optimal benchmark for the flatness of the profile achieved in the second stage. Secondly, in the operational stage of event-based profile steering the algorithm assigns EVs individual schedules upon their arrival in an iterative process with the following steps: Initialize $\vec{x} = \vec{0}$ as the aggregated power profile of the EVs scheduled thus far (namely none). Upon arrival, an EV is assigned a load profile $\vec{y}$ that minimizes $||\vec{p}-(\vec{x}+\vec{y})||_2$, i.e., that minimizes the square of the difference between scheduled load and target profile, while considering constraints (e.g., departure time and electricity requirement). Update $\vec{x} = \vec{x}+\vec{y}$. We repeat until the end of the time horizon, or until all EVs have arrived.

To integrate charging guarantees as default and the veto-button as an opt-out into event-based profile steering, we differentiate between controlled and uncontrolled EVs. For controlled EVs, upon their arrival, $\vec{y}$ is determined under the constraint that EV-specific guarantees are respected. In the office location case study, we assume guarantees of providing employees with sufficient charge for their work-home commute within six hours of charging. For uncontrolled EVs, $\vec{y}$ is the power profile where the EV immediately charges at maximum power until the battery is full or the EV departs. Note that the electricity volume differs depending on whether an EV is controlled or uncontrolled. In the former case, the EV receives sufficient charge for the work-home commute, while in the latter the battery is charged till full.

Simulations are run using DEMKit, a cyber-physical energy management toolkit [13]. All numeric inputs are based on the infrastructure available at the physical parking lot in Utrecht, as well as real data collected there. Maximum charging powers per EV are assumed to be 11kW, and we use a power capacity of 1.3 MW as benchmark based on the contracted grid connection limit (2.0 MW) reduced by the typical building load (1.6 MW), and increased by the maximum production capacity of the PV installation (0.9 MW). Furthermore, we have access to charging session data that per session specifies the user ID, arrival time, departure time, and energy charged. Throughout 2022, up to 100 charging sessions were registered in a single day. Next to this, we conducted a survey among the EV-driving employees. Out of the 90 respondents, 45 provided their user ID, making it possible to connect their responses to their charging session data. In particular, their response includes their work-home commute distance[1]. Using a default driving efficiency of 199 $\frac{\text{Wh}}{\text{km}}$ [14], we used this information to estimate the charge for work-home commute per employee.

In the numerical experiments, we simulate operation with 400 EVs over a time horizon of one day where we consider that we have commute distance information for the controlled EVs, and that the other EVs are uncontrolled EVs. To make sure that we always have an EV population of 400 EVs, we perform a sweep over the fraction of controlled versus uncontrolled EVs. If $x\%$ of the EV population is controlled, we sample the $x\% \cdot 400$ most recent sessions with and the $(100-x)\% \cdot 400$ most recent sessions without work-home commute information from the augmented data set[2].

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[1] A full list of survey questions is available under https://github.com/lwinschermann/OfficeEVparkingLot-SurveyQuestions.

[2] Code to process and sample data, generate DEMKit input and evaluate the simulated output is available under https://github.com/lwinschermann/OfficeEVparkingLot

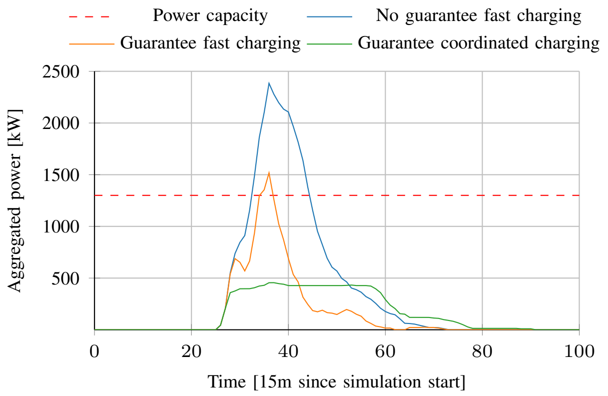


Fig. 1: Aggregated power plots for an office parking lot use case with charging guarantee for 400 EVs.

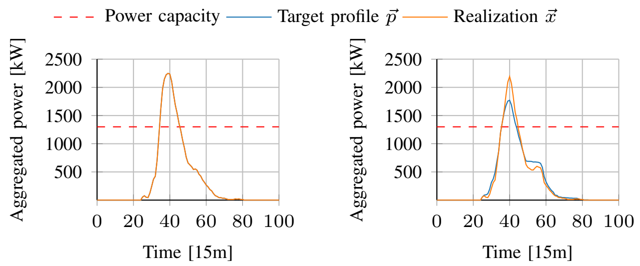
III. RESULTS

In this section, we present the simulation results for the office building parking lot use case. We first present results focused on charging guarantees, after which we consider EV populations with both controlled and uncontrolled EVs.

First, we focus on the effect of introducing guarantees to the office parking lot use case. Fig. 1 illustrates the aggregated power of 400 EVs that charge according to different policies. The blue line shows the case of charging at maximum power until an EV's battery is full or it departs, whereas in the orange case EVs charge at maximum power until their individual work-home commute charge is supplied. In the green scenario, EVs charge their work-home commute in a coordinated manner, within six hours. The red dashed line indicates the assumed power capacity of 1.3 MW.

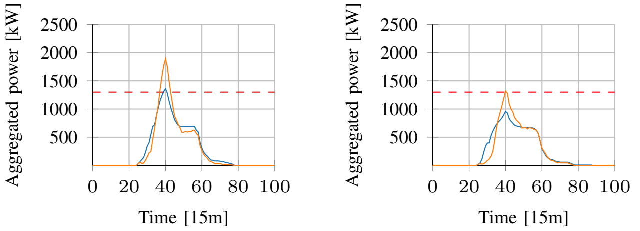
As can be seen, the blue uncontrolled scenario significantly exceeds the 1.3 MW power limit, peaking at almost 2.4 MW. Reducing the electricity provided to individual EVs to their work-home commute charge reduces the peak to just above 1.5 MW (orange line). While evidently reducing both the extent and the duration of power limit violations, the resulting aggregated power profile still violates power constraints. When applying control to the scenario (green line), we do not only get a feasible profile, it remains at power levels around 0.45 MW. Remember that the benchmark power limit considers 0.4 MW available from the grid connection alone. Compliance with 0.4 MW therefore translates to a feasible schedule even on days without local generation of electricity. Interestingly, we observe increased charging in the tail of the (green) profile, compared to the orange and blue curves. This is due to the coordinated delay of charging, and reflects on the relatively long stays associated with near-office parking.

The influence of including veto-buttons into the charging policy is illustrated in Fig. 2. Hereby, for fractions of 0, 20, 40, 60, 80 and 100% controlled EVs, two different situations are presented. In detail, the red-dashed line indicates the power capacity, the blue line represents the aggregated target profile $\vec{p}$ resulting from the first (offline) stage of event-based profile steering, and the orange line gives the aggregated power profile $\vec{x}$ of the second (online) stage of event-based profile steering. In the specific setup of this paper, the blue line also serves as indication of the flattest profile that can be achieved given perfect information on the EVs and their charging requirements. As illustrated in the figure, the higher the percentage of controlled EVs, the lower the power peaks. However, the total energy served (surface under blue and orange lines) is decreasing in the percentage of controlled EVs, since those EVs only receive their home-commute charge.



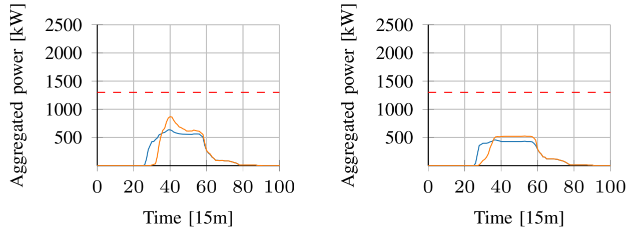
(a) Percentage controlled = 0%

(b) Percentage controlled = 20%



(c) Percentage controlled = 40%

(d) Percentage controlled = 60%



(e) Percentage controlled = 80%

(f) Percentage controlled = 100%

Fig. 2: Aggregated power plots for the office parking lot use case with integrated charging guarantee and veto-button for varying percentages of controlled and uncontrolled EVs.

Considering the target profile in the first stage (blue line), all graphs that include uncontrolled EVs show power peaks deviating from the otherwise flattened profile. Those peaks occur during the early office hours, when multiple uncontrolled EVs arrive and charge at maximum power, as expected for high percentages of uncontrolled EVs. However, EVs utilizing the veto-button receive their full charge, as opposed to controlled EVs that receive their home-commute charge. This implies that the percentage of electricity corresponding to uncontrolled EVs decreases slower than the fraction of uncontrolled EVs in the population. Subsequently, peaks in the aggregated power profile also occur for higher percentages of controlled EVs, since the controllable electricity volume is not sufficient to

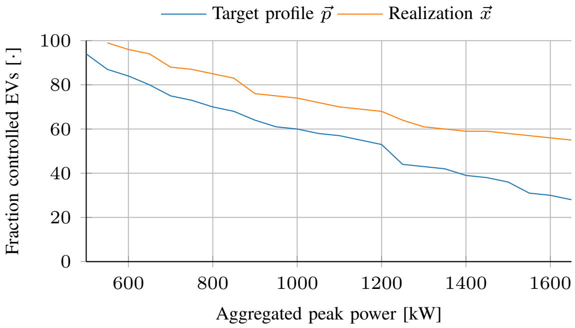


Fig. 3: Per power capacity, minimum fraction controlled EVs in population such that resulting aggregated power profile complies with capacity limit.

smooth out the uncontrolled loads.

We observe two weaknesses that come with applying event-based profile steering to a use case that combines controlled and uncontrolled loads. Firstly, peaks are amplified in the second stage where each EV is scheduled upon arrival (orange line). In the graphs with 20, 40, 60, and 80% controlled EVs, the corresponding (orange) realization $\vec{x}$ clearly exceeds the (blue) target profile $\vec{p}$. The iterative approach of event-based profile steering schedules EVs at times with the highest difference between target profile $\vec{p}$ and already scheduled load $\vec{x}$. Therefore, the first arriving EVs are scheduled to charge during the planned peaks halfway through the planning horizon. However, the peaks occur due to uncontrolled EVs that have not yet arrived, resulting in amplified peaks. Secondly, we observe that in the realized planning $\vec{x}$, EVs start charging later than in the optimal planning. That is again due to early EVs being scheduled during the later occurring peaks.

Overall, we see that even when allowing veto-buttons, the proposed control stays within power limits. In the presented case the realized profile $\vec{x}$ stays within power limits if at least 61% of the population are controlled EVs. For target profile $\vec{p}$, the same threshold lies at 43% controlled EVs. Note that this percentage is highly dependent on the given maximum capacity. To this end, Fig. 3 illustrates the trade-off between the power limit against the minimum fraction of controlled EVs such that the planning under event-based profile steering does not violate capacity constraints. In particular, the blue line illustrates this trade-off for the flattest possible profile.

IV. PRACTICAL ADD-ONS

The framework presented in Section II-A can be tailored to specific use cases, as demonstrated for a fixed set of assumptions above. This section presents considerations that can be taken into account when applying the framework to other office location use cases that may have other requirements.

- Guaranteed electricity: To determine the amount of electricity to be guaranteed, one may consider to provide enough electricity for single-trip or round-trip commute, offer electricity packages that employees can sign up for, or to guarantee a static amount of electricity to everyone.
- Guarantee deadline: To determine within what time frame to provide the guaranteed electricity, one may consider employment contracts (e.g., full-time, part-time, home office days) and whether to use dwell time or departure time (e.g., within 6 hours or by 5pm).
- Data management: To determine how to collect, curate and change (commute) data, one may consider employee portals or HR-internal administration.
- Energy efficiency: To determine the amount of electricity needed for a given work-home commute distance, one may consider to determine the electricity based on constant efficiencies, vehicle-dependent efficiencies, and taking seasonal variances into account.
- Veto-button: To implement the veto-button, one may consider the amount of electricity to provide (e.g., full-charge or commute charge), the physical implementation (e.g., at the charger, reception, in an online employee environment, or (strategic) placement of dedicated fast charging stations) and the transaction price per unit of electricity with or without pressing the veto-button.
- Framing: In communication with users, one may consider a green perspective, a limited resources perspective and a financial incentive perspective.
- Optimization objective: One may consider to maximization self-consumption of locally produced electricity, to maximize the integration with (the office building's) other power loads, to implement price-based control, or to minimize peaks at the grid connection.
- Optimization method: To determine which control mechanism to use, one may consider how to distribute excess energy past the guaranteed charges.
- Application of framework: The proposed framework may be applied to daily operation, to determine the number of EV stations that a location can host, to determine the number of uncontrolled EVs that can be supported, and to operate parking lots with hybrid populations of for example employees and visitors.

V. DISCUSSION

In the following, we first reflect on the proposed general framework, followed by the specific office parking lot use case.

Firstly, the combination of guarantees and veto-buttons increases transparency and control for the end user. In particular, the veto-button allows users whose needs are not covered by a specific guarantee to overrule the used parameters. As we have seen in the given use case, from an aggregator point of view we only need a certain minimum amount of controlled EVs for the method to remain feasible.

Independent of the chosen setup of the guarantee and veto-button, communication remains crucial. All efforts to build trust are in vain if users do not understand why their EV was not fully charged during the charging session. Furthermore, as the population of EV drivers is extending from early adapters and technology enthousiasts to drivers with limited intuition about the relation between state of charge, kWh and commute distance in km, grid capacity or how all of those in turn relate to (seasonal/periodic) variations, it has to be observed how this change may influence the user behaviour of the overall population of EV drivers. Such considerations were left out of scope for now, but should be taken into account when applying the framework to a practical use case.

Looking at the presented office building use case, there are various limitations to be considered. Firstly, the sample size of EV drivers whose home-commute we can match to the charging session data is limited to 45 responses. That is partially due to the fact that half of the survey responses cannot be associated with a user ID. Furthermore, the chosen default efficiency of $199\frac{\mathrm{Wh}}{\mathrm{km}}$ is an average value reported for fully electric vehicles, whereas hybrids are common at the pilot site. That situation may change significantly in the coming years. As we have no additional information on the difference in charging and driving behaviour between fully electric and hybrid drivers at that specific location, this factor needs to be taken into account when implementing solutions.

On a more global level, it has to be noted that the power limit used as a reference for the parking lot is optimistic. On top of the base capacity available to the parking lot, we assume full PV production throughout the day. However, in general power demand peaks in largely uncontrolled EV populations do not necessarily coincide with PV production peaks. Therefore, considering the variability of charging power capacity, the need for coordinated charging becomes evident. While the guaranteed amount of charge may be seen as quite conservative when comparing the electricity provided with what would fit the battery, it is a suitable tool to overcome information gaps and deal with limited power capacity.

VI. CONCLUSION

To implement EV charging strategies, communication with and integration of users is crucial. We propose a framework of charging guarantees and veto-buttons to promote transparency, trust and control from a user perspective. As validated for an office parking lot use case with 400 EVs based on real data, a charging guarantee of supplying within 6 hours sufficient energy to facilitate work-home commute facilitates the parking lot to stay within the power limit of its grid connection. Furthermore, many charging strategies require information on electricity requirement and departure times of EVs which in practice are usually unknown. The parameters set by the guarantee bridge those information gaps of electricity requirement and departure time per EV. We also demonstrate that controlling around 60% of the EV population suffices to allow for the integration with veto-buttons opting for fast charging of the full electricity requirement in office parking lot settings. Both the guarantee and veto-button frameworks may be effectively adapted to specific use cases.

A crucial extension for future research is to include user input in the system. This applies to the design of guarantees, as well as the validation of their effect in practice. Furthermore, research into the frequency with which veto-buttons are utilized is necessary. Such information will make it possible to apply the framework to scale the amount of chargers a parking lot can host, given power capacity constraints. The utilization is a use case specific factor and needs to be investigated as such. In the office parking lot case, for example, business trips, child-care and part-time work hours may be reasons for early departure, and the frequency of their occurrence is yet to be determined and likely differs per office and industry. Lastly, the presented research points to short-comings of event-based profile steering. For our use case, performance improvements may be achieved by adapting that methodology. Alternatively, choosing an online fill-level approach or prediction-based algorithm [15] may be more suitable for populations with both controlled and uncontrolled EVs. Such an approach would also allow to distribute excess energy among present EVs if PV production exceeds the volume predicted for the planning.

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