Robust and Predictive Charging of Large Electric Vehicle Fleets in Grid Constrained Parking Lots

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***Abstract*—Grid congestion forms an obstacle for the adoption of electric vehicles (EVs) by companies for their sustainability goals. This paper presents a robust approach to smart charging of large fleets of EVs that only utilizes currently available technologies and data, such that it can be applied in practice. The method relies only on available data at charge point operators. The presented approach uses offline aggregated planning to determine a robust fill-level. Subsequently, this fill-level is used in online control to maximise the quality of service to users while being able to provide flexibility to the energy system. Simulation results using real data show that the self-consumption of PV energy can be improved from 72.0% to 85.4%. Furthermore, the energy not served is reduced from 5.9% to 2.8%.**

***Index Terms*—electric vehicles, optimisation, smart grids**

I. Introduction

In order to reach the climate goals, the European Union has recently agreed to ban the sales of new diesel and petrol cars by 2035 [1]. In many countries, such as the Netherlands, the market share of electric vehicles (EVs) is already rapidly increasing due to lower costs and subsidies, especially among leased company cars. As a result, more parking lots at offices are being equipped with many charging stations. However, one potential problem is the lack of capacity in the local distribution grids due to ongoing electrification efforts. Currently, many companies cannot be provided with a larger grid connection to provide energy to the expanding fleet of EVs. However, installing charging infrastructure is often combined with the installation of PV arrays on top of the parking lot. This is a potential win-win to alleviate the burden of a limited grid connection as working hours and the production of solar energy coincide. Hence, optimal control of EV charging becomes an essential technology for companies to meet their, sometimes mandatory, sustainability goals.

Many methods for optimal coordinated control of EV charging have been presented in recent years as surveyed by [2], [3]. However, many solutions depend on the availability of information such as the state of charge (SoC), requested energy, and departure time. In practice, this information is not available (i.e., current AC charging protocols do not provide SoC information) or is hard to obtain (i.e., they rely on high end-user participation). Other methods are computationally inefficient to quickly (re-)optimize larger fleets of hundreds of EVs to react to intermittent production of PV energy. On the positive side, Van der Klauw [4] developed efficient scheduling algorithms for several classes of buffer devices. Combined with the decentralized optimization methods, such as ADMM [5] or Profile Steering [6], a large fleet of EVs can be steered efficiently. Furthermore, an efficient and robust algorithm for optimal EV charging is presented by Schoot Uiterkamp et al. [7], in which the optimal solution is characterized by a single value, called the fill-level that is used for online control of a single EV. Vandael et al. [8] and De Craemer et al. [9] have presented a three-step approach in which constraints of a large fleet of EVs are centrally aggregated first to find a global optimal power trajectory. Subsequently, this solution is used in an online control setting to control individual EVs based on their respective charging priority. However, Appino et al. [10] note that the employed aggregation method may lead to infeasible solutions.

Still a practical and pragmatic solution is urgently needed to facilitate the energy demands of rapidly increasing EV fleets in capacity constrained power grids. Therefore, this work presents a practical and robust control framework for the charging of large fleets (100+) of frequently returning EVs in parking lots with a limited grid connection capacity. Our solution works with technology currently available on the market, only relies on readily available information from the charge point operator (CPO) back-end system, and does not need interaction with the end-users. The method employs an offline planning phase, based on historical data, to find an optimal power profile for the parking lot as a whole. This is done using an algorithm of which its time complexity only depends on the number of considered time intervals. Subsequently this profile is used to robustly control individual EVs based on their estimated priority and real-time measurement data. This study utilizes charging session data and technical properties from a real-world large scale charging facility [14]. The main contributions of this work are a framework that:

- is highly scalable with large numbers of EVs;
- only requires readily available technologies;
- is robust to forecasting errors by real-time adaptation.

The remainder of this paper is organized as follows: Section II presents the available data models and simulation models. Section III presents the optimization framework, consisting of (i) an aggregated offline optimization, and (ii) an online control heuristic. Subsequently, Section IV presents a simulation study using a real-world use case. Finally, conclusions and future work are presented in Section V.

II. Model

This section presents the models for EV charging transactions and the parking lot itself, including the details on generally available data for these models.

A. Charging Transactions Model

The purpose of this work is to enable the best possible service to users of a parking lot for their individual charging sessions i.e., provide the requested energy before departure. Each (finished) charging transaction $m \in M$ can be characterized by the following information: arrival time m_{A}, departure time m_{D}, energy served m_{E}, maximum drawn power m_{P}, and an user identification number m_{ID}. This is the historical information that is generally available in a CPO back-end system and is therefore the data our method relies on.

Upon arrival of an EV i.e., the moment a new transaction is *started*, only m_{A} and m_{ID} are known. A transaction m is said to be *active* for discrete time intervals $T_m = \{m_{\mathrm{A}}, \ldots, m_{\mathrm{D}} - 1\} \in \mathcal{T}$, where $\mathcal{T} = \{1, 2, \ldots, T\}$ denotes the set of T discrete time intervals. The set of active transactions at time t is denoted by $M_t \subseteq M$. Note that m_{D} only becomes known at the actual moment the EV departs or the EV ends the transaction due to a full battery.

B. EV Model

For simulation purposes, we introduce the following discrete time model for EVs. Consider an EV m^{EV} that is linked to transaction m. This EV can be characterized by a battery capacity $m_{\mathrm{C}}^{\mathrm{EV}}$, maximum power rating $m_{\mathrm{P}}^{\mathrm{EV}}$, and SoC upon arrival $m_{\mathrm{SoC}}^{\mathrm{EV}}$. If $\mathbf{x}_m = (x_{m,1}, x_{m,2}, \ldots, x_{m,T})$ is the power drawn by a transaction m ($x_{m,t} = 0, \forall t \notin T_m$), then the SoC $m_{\mathrm{SoC},t'}^{\mathrm{EV}}$ at time t' can be obtained by:

$$m_{\mathrm{SoC},t'}^{\mathrm{EV}} = m_{\mathrm{SoC}}^{\mathrm{EV}} + \sum_{t=m_{\mathrm{A}}}^{t'-1} x_{m,t} \tag{1}$$

Subject to the following constraints:

$$0 \leq x_{m,t} \leq m_{\mathrm{P}}^{\mathrm{EV}} \quad \forall t \in T_m \tag{2}$$

$$0 \leq m_{\mathrm{SoC},t}^{\mathrm{EV}} \leq m_{\mathrm{C}}^{\mathrm{EV}} \quad \forall t \in T_m \tag{3}$$

The conversion from power to energy is omitted in the formulations for ease of readability. It is important to note that none of the m^{EV} parameters presented in this subsection can currently be obtained or controlled (easily) in practice using existing communication interfaces. Only the power drawn can be influenced by controlling the charging station power supply.

C. Parking Lot Model

Larger EV charging parking lots are characterized by the fact that they often have multiple rows with parking spots that are equipped with charging stations. The power capacity of the infrastructure (cables, protection, and transformers) is often lower than the total power capacity of chargers installed. Hence, power constraints must be met at different infrastructure layers of a parking lot.

For this, each row $r \in R$ is characterized by its number of charging stations r_{N}, each with a power limit $\overline{r_{\mathrm{P}}}$. Furthermore, the total power limit of a row $\overline{r}$ is often even more restrictive, i.e. $\overline{r} < r_{\mathrm{N}} \cdot \overline{r_{\mathrm{P}}}$. An balanced three phase power system with three phase chargers is assumed in this work.

Arriving EVs can only connect to a free charging spot. Let $M_{r,t} \subseteq M_t$ be the set of active transactions within row r at time t. Then it must hold that $0 \leq |M_{r,t}| \leq r_{\mathrm{N}}, \forall t \in \mathcal{T}$. Arriving EVs are assigned to a random row from the set of rows that are not fully occupied (i.e., $|M_{r,t}| < r_{\mathrm{N}}$) and let m_r be the row to which m is connected. Note that we assume here that EVs immediately leave the parking lot as soon as their transaction is ended.

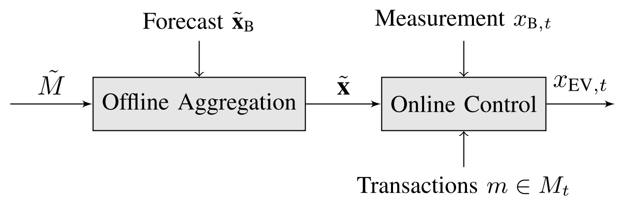


Fig. 1. Steps and information flow of the presented framework.

A parking lot is connected to the main grid that has a limited connection with upper power bound $\overline{x}$ and lower bound $\underline{x}$. Often, this connection is more limiting such that $\overline{x} < \sum_{r \in R} \overline{r}$. Furthermore, it may share this common resource with other loads and generation, such as office buildings. We denote this building load by a vector $\mathbf{x}_{\mathrm{B}} = (x_{\mathrm{B},1}, x_{\mathrm{B},2}, \ldots, x_{\mathrm{B},T})$, where negative values indicate generation.

The aggregated EV load is denoted by $\mathbf{x}_{\mathrm{EV}} = (x_{\mathrm{EV},1}, x_{\mathrm{EV},2}, \ldots, x_{\mathrm{EV},T})$, where $x_{\mathrm{EV},t} = \sum_{m \in M_t} x_{m,t}$. The load for row r is given by $x_{\mathrm{r},t} = \sum_{m \in M_{r,t}} x_{m,t}$, and the total load $\mathbf{x} = (x_1, x_2, \ldots, x_T) = \mathbf{x}_{\mathrm{EV}} + \mathbf{x}_{\mathrm{B}}$. To this, the following constraints apply:

$$0 \leq x_{\mathrm{r},t} \leq \overline{r} \quad \forall r \in R, \forall t \in T \tag{4}$$

$$\underline{x} \leq x_t \leq \overline{x} \quad \forall t \in T \tag{5}$$

III. Framework

This section presents the overall control framework, which consists of an offline planning phase and online control phase as shown in Fig. 1. The offline planning utilizes aggregate modeling and optimization of the fleet of EVs to determine an target power profile $\tilde{\mathbf{x}}$ for the total connection load, and is made upfront for e.g., day-ahead planning. This profile serves as a time-varying variant of the fill-level as described in [7] and for larger EV fleets is expected to be robust against forecast errors. Subsequently, the charging stations are controlled in such a way that the total observed power $\mathbf{x}$ approximates $\tilde{\mathbf{x}}$ by applying an online control policy. This policy is based on a priority metric for each individual transaction m, which is determined using historical observations for m_{ID}.

A. Offline Aggregated Planning

The goal of the offline planning phase is to obtain a planned profile $\tilde{\mathbf{x}}$ that minimizes an objective function f, e.g., for day-ahead energy buying or to minimize the carbon footprint by optimally utilizing locally generated solar energy. In order to obtain $\tilde{\mathbf{x}}$ we assume a forecast of the load $\tilde{\mathbf{x}}_{\mathrm{B}}$ and transactions $\tilde{M}$ to be available (for sake of clarity we denote all forecasted (and thus uncertain) values with a tilde (˜)). We employ an aggregate modeling technique to avoid scalability issues as proposed in [8]. Furthermore, we note that individual optimization does not make sense as it is uncertain which EV will be arriving, when, and at which row in R. Instead, we assume that the aggregate of a fleet of EVs in the whole parking lot is more predictable and therefore more robust.

The behaviour of an aggregated fleet of EVs can be viewed as a leaky buffer, in which energy is withdrawn from the system by departing EVs. For such problems, the *optBC* algorithm presented in Chapter 5 of [4] with time complexity $\mathcal{O}(T^2)$ can be used. To use this algorithm, lower capacity $\tilde{\underline{\mathbf{c}}}$ and upper capacity $\tilde{\bar{\mathbf{c}}}$ bounds need to be obtained. These bounds represent the energy that must and can be charged up to time t respectively. For each forecasted transaction $\tilde{m} \in \tilde{M}$ these bounds are obtained as follows:

$$\begin{aligned}\tilde{\underline{\mathbf{c}}}_{\tilde{m}} &= \{\tilde{\underline{c}}_{\tilde{m},t} | \tilde{\underline{c}}_{\tilde{m},t} = \min(\tilde{m}_{\mathrm{E}}, \\ &\quad \max(\tilde{m}_{\mathrm{E}} - \tilde{m}_{\mathrm{P}} \cdot (\tilde{m}_{\mathrm{D}} - 1 - t), 0)), \forall t \in \mathcal{T}\} \quad (6)\\ \tilde{\bar{\mathbf{c}}}_{\tilde{m}} &= \{\tilde{\bar{c}}_{\tilde{m},t} | \tilde{\bar{c}}_{\tilde{m},t} = \max(0, \\ &\quad \min(\tilde{m}_{\mathrm{P}} \cdot (t - \tilde{m}_{\mathrm{A}}), \tilde{m}_{\mathrm{E}})), \forall t \in \mathcal{T}\} \quad (7)\end{aligned}$$

The aggregated bounds are found using:

$$\tilde{\underline{\mathbf{c}}} = \sum_{\tilde{m} \in \tilde{M}} \tilde{\underline{\mathbf{c}}}_{\tilde{m}} \quad (8)$$

$$\tilde{\bar{\mathbf{c}}} = \sum_{\tilde{m} \in \tilde{M}} \tilde{\bar{\mathbf{c}}}_{\tilde{m}} \quad (9)$$

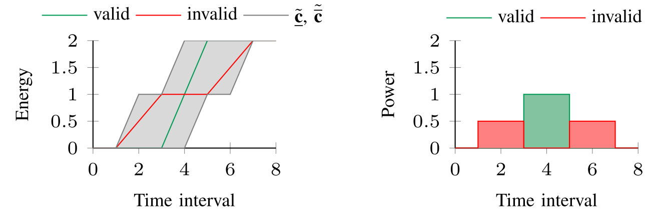
Furthermore, we have to take into account the maximum power $\tilde{\bar{\mathbf{x}}}_{\mathrm{EV}} = (\tilde{\bar{x}}_{\mathrm{EV},1}, \tilde{\bar{x}}_{\mathrm{EV},2}, \dots, \tilde{\bar{x}}_{\mathrm{EV},T})$ with which the EVs can be charged, which depends on the connected EVs, the load $\tilde{\mathbf{x}}_{\mathrm{B}}$, and the connection constraint $\bar{x}$:

$$\tilde{\bar{x}}_{\mathrm{EV},t} = \min(\bar{x} - \tilde{x}_{B,t}, \sum_{\tilde{m} \in \tilde{M}_t} \tilde{m}_{\mathrm{P}}) \quad \forall t \in \mathcal{T} \quad (10)$$

Note that in this work we simplify the model by using balanced three-phase charging, omitting vehicle-to-grid functionality, and assume the lower bound ($\underline{x}$) not to be a limiting factor. Using this input and the *optBC* algorithm, we find the optimal power profile for the fleet as $\tilde{\mathbf{x}}_{\mathrm{EV}} =$ *optBC*$(f, \tilde{\bar{\mathbf{x}}}_{\mathrm{EV}}, \tilde{\underline{\mathbf{c}}}, \tilde{\bar{\mathbf{c}}})$. We refer the reader to Chapter 5 in [4] for more details on this algorithm. For the main connection load we now get $\tilde{\mathbf{x}} = \tilde{\mathbf{x}}_{\mathrm{EV}} + \tilde{\mathbf{x}}_{\mathrm{B}}$.

1) Infeasible solutions: As noted in [10], this aggregated method does not guarantee that the outcome is feasible. An intuitive counterexample can be constructed by considering two transactions $\tilde{M} = \{a, b\}$, with $a_{\mathrm{C}} = 1 \geq b_{\mathrm{C}} = 1$ and $a_{\mathrm{P}} = b_{\mathrm{P}} = 1$. Furthermore, let the arrivals be $a_{\mathrm{A}} = 1 < b_{\mathrm{A}} = 3$ and departures be $a_{\mathrm{D}} = 7 > b_{\mathrm{D}} = 5$. Fig. 2 shows a possible infeasible solution by charging only in intervals in which b is not active ($\{1, 2, 5, 6\}$). For large enough fleet sizes it is expected that this is not a problem in practice. In Section IV-A we will analyse the impact of the applied constraint relaxation.

2) Resource augmentation: It is expected that forecasting errors cause more problems. Schoot Uiterkamp et al. [7] have shown that the robustness of the solution increases significantly with a slightly overestimated fill-level. Overestimation means that it is likely that the transactions will be finished charging earlier. This is generally desired as it avoids the risk of high power peaks and/or not being able to serve all transactions. In our case, we can achieve this overestimation by substituting $\tilde{m}_{\mathrm{E}}$ with $\alpha\tilde{m}_{\mathrm{E}}$ and $\tilde{m}_{\mathrm{P}}$ with $\beta\tilde{m}_{\mathrm{P}}$, and choosing $\alpha > 1$ (expected energy request will be higher) and $0 < \beta < 1$ (adds robustness against lower maximum powers).



(a) Energy (b) Power

Fig. 2. Graphical representation of constraint aggregation and a valid and invalid solution for 2 transactions a and b. Here, $a_{\mathrm{A}} = 1$, $a_{\mathrm{D}} = 7$, $b_{\mathrm{A}} = 3$, and $b_{\mathrm{D}} = 5$. It is clear that in the invalid solution no power is delivered in intervals where b is active. Hence b receives no energy and a is overcharged.

B. Online Control

During the operational phase, the goal is to control the charging stations such that the total power $\mathbf{x} \approx \tilde{\mathbf{x}}$. In this paper we do so by using an online control heuristic that selects which EVs receive power given their priority and the capacity limits. Control of charging stations in this study is limited to on/off control (i.e., $x_{m,t} \in \{0, m_{\mathrm{P}}^{\mathrm{EV}}\}$) to avoid additional energy losses, with an already limiting connection, due to charging inefficiencies at lower charging powers [11].

1) EV Prioritization: To select which EVs receive power and which not, a way of prioritization is required. This prioritization reflects which EVs should be served first to ensure that they will receive the desired energy before departure. Many methods for prioritization of tasks are proposed in literature. A comprehensive study of different methods is presented in [12]. However, the priority metric proposed in [13] provides overall better performance. We define the priority z_t^m of an active transaction $m \in M_t$ at time t as:

$$z_t^m = \frac{\tilde{m}_{\mathrm{E}} - m_{\mathrm{E},t}}{(\tilde{m}_{\mathrm{D}} - t) m_{\mathrm{P}}} \quad \forall m \in M_t \quad (11)$$

Where $m_{\mathrm{E},t} = m^{\mathrm{EV}}_{\mathrm{SoC},t} - m^{\mathrm{EV}}_{\mathrm{SoC}}$ is the energy served by the charging station up to time t, and m_{P} can be assumed to be known utilizing the first power measurement. Two unknown values remain: the estimated total energy demand $\tilde{m}_{\mathrm{E}}$, and the estimated departure time $\tilde{m}_{\mathrm{D}}$. These have to be learned from prior transactions initiated by the same m_{ID}, which we further discuss in Section IV.

The framework also allows for incorporation of information provided by users e.g., using an app or communication interfaces, to retrieve $\tilde{m}_{\mathrm{E}}$ and $\tilde{m}_{\mathrm{D}}$. Users that opt-out of smart charging (e.g., because they need to have their EV charged urgently) can be intergrated by setting $z_t^m = \infty$. This preserves the load-balancing functionality to avoid grid overloading.

2) Control Heuristic: For the control policy, it is important to control the charging stations in such a way that none of the limits are violated while ensuring the transactions are served in a fair manner. This means that we wish to serve transactions with the highest z_t^m as much as possible with the total load approximating $\tilde{\mathbf{x}}$. The upper bound $\overline{x}_{\mathrm{EV},t}$ is defined as follows:

$$\overline{x}_{\mathrm{EV},t} = \min(\overline{x}, \tilde{x}_t + \gamma) - x_{\mathrm{B},t} \quad \forall t \in \mathcal{T} \tag{12}$$

Where $\gamma = \frac{1}{2}\overline{r_{\mathrm{P}}}$ is a factor to allow for small overshoots at half of the charger power rating due to on/off control. The load $x_{\mathrm{B},t}$ can be approximated using real-time measurements and the known previous control action, i.e. $x_{\mathrm{B},t} \approx x_t - x_{\mathrm{EV},t-1}$.

The control algorithm (see Algorithm 1) is executed each time step and starts by initializing all chargers to be turned off ($x_{\mathrm{EV},t} = 0$). Z_t is an ordered list of transactions $m \in M_t$ in decreasing order by their associated priority z_t^m. In an iterative manner we take the first transaction m from Z_t and turn on the associated charger ($x_{\mathrm{EV},t} = x_{\mathrm{EV},t} + m_{\mathrm{P}}$) if this is feasible according to constraints (4) and (5). Subsequently m is removed from Z_t. We continue iterating until $Z_t = \emptyset$ or $x_{\mathrm{EV},t} + m_{\mathrm{P}} > \overline{x}_{\mathrm{EV},t}$. The presented algorithm hereby only implements the real-world solution that uses data supplied by the CPO and therefore excludes simulation logic.

Algorithm 1 Online control algorithm for $\mathbf{x} \approx \tilde{\mathbf{x}}$

```
function ONLINE CONTROL(x̃, x_B, x̄, 𝒯, R, M)
    for t ∈ 𝒯 do
        {Initialization}
        x_EV,t ← 0
        x_r,t ← 0, ∀r ∈ R
        x̄_EV,t ← min(x̄, x̃_t + γ) − x_B,t
        Obtain sorted list Z_t based on z_t^m, ∀m ∈ M_t
        {Iterative process}
        while |Z_t| ≠ ∅ ∧ x_EV,t ≤ x̄_EV,t do
            Take the first m from Z_t
            Z_t ← Z_t \ {m}
            x*_m ← min(m_P, r̄_P)
            r ← m_r {row where m is connected}
            if x_r,t + x*_m ≤ r̄ ∧ x_EV,t + x*_m ≤ x̄_EV,t then
                x_m,t ← x*_m
                x_r,t ← x_r,t + x*_m
                x_EV,t ← x_EV,t + x*_m
            end if
        end while
    end for
end function
```

IV. Evaluation

We evaluate the presented approach using a real-world use case of an office building in Utrecht, the Netherlands [14]. This parking lot will host 343 AC chargers, of which most are already operational. Furthermore it has a PV array with a peak power of 840 $\mathrm{kW_p}$. The available capacity to the main grid is limited to $\overline{x} = 0.4$ MW. From this site, a data set with 13753 historical charging transactions (after filtering) is available, of which 11226 are used for a training set $\hat{M}$ (81.6%). Furthermore, the data set only contains transactions of users that have at least finished 10 charging sessions, of which at least 8 are part of the training set.

TABLE I
Comparison between aggregated versus exact optimization

	Difference [W]			**Optimization Time [s]**			
	RMSE			*Using [15]*			*Agg*
$\lvert M\rvert$	min	mean	max	min	mean	max	mean
10	0.00	11.97	228.88	0.021	0.062	0.106	0.003
25	0.00	7.24	93.93	0.084	0.265	0.457	0.004
50	0.00	7.50	66.67	0.302	0.696	1.693	0.005
100	0.01	5.85	22.19	0.895	1.712	4.070	0.006
250	0.31	6.12	17.70	4.397	7.135	20.321	0.008
500	0.46	4.62	11.25	14.038	23.365	33.774	0.008

We use a simplified model of the parking lot to evaluate the performance of the proposed approach with the following parameters: $|R| = 11$ rows with $r_{\mathrm{N}} = 32$, $\overline{r}_{\mathrm{P}} = 22$ kW, and $\overline{r} = 175$ kW. The baseload $\mathbf{x}_B$ consists of a PV power profile recorded on a partly cloudy day (May 6th 2023) in a minute resolution from the real-world SlimPark site [14], for which a day-ahead forecast is used in the offline planning phase. This profile is scaled to match the specifications of the target parking lot, resulting in a forecasted PV generation of 3.5 MWh and an actual realization of 3.3 MWh. We simulate one full day in time intervals of 1 minute (i.e., $T = 1440$). The objective for this study is $\min f = \min \| \mathbf{x}_{\mathrm{EV}} + \mathbf{x}_{\mathrm{B}} \|_2$, i.e., match local production and avoid power peaks.

A. *Offline Planning*

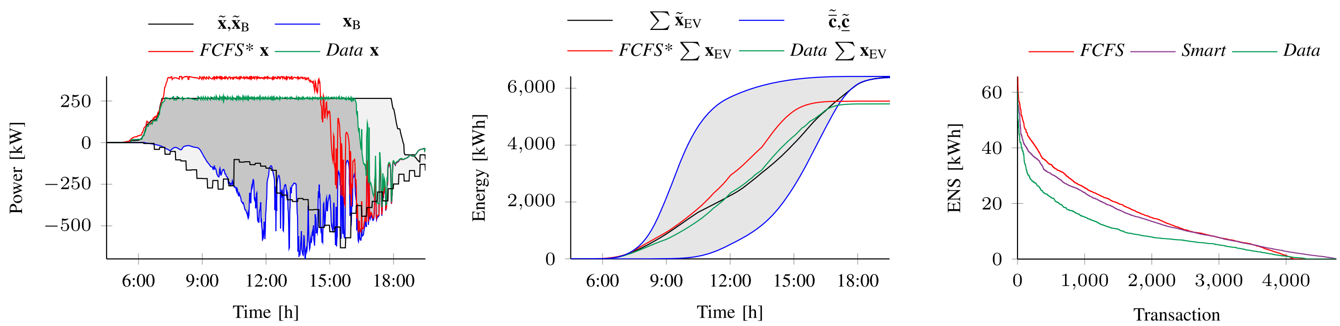
We first evaluate the accuracy of the aggregated offline planning with feasible solutions found by the Profile Steering heuristic presented in [15] and the EV planning from [4]. For this we draw random charging transactions from the complete data set. A parameter sweep is conducted where the number of transactions $|M|$ is varied and $\frac{10000}{|M|}$ runs are executed for each value of $|M|$ using an AMD Ryzen 9 7900X processor and Python implementation. The results are normalized by division by $|M|$. Table I shows the root mean squared error (RMSE) between the two approaches and provides the total execution time for the method presented in [15] and the aggregated method presented in Subsection III-A (denoted by *Agg*). On the one hand, it is clear that the RMSE is negligible for larger fleets of EVs, meaning that the feasibility problems are no major issue with the presented approach. On the other hand, the achieved reduction in total computation time is significant.

B. *Online Control Prioritization Methods*

What remains for online control is to estimate the unknown transaction parameters for departure time $\tilde{m}_{\mathrm{D}}$ and requested energy $\tilde{m}_{\mathrm{E}}$ for each individual user as described in Subsection III-B. Four different online control methods are evaluated:

1) Perfect Information (Perfect): In this approach perfect information is assumed, i.e. $\tilde{m}_{\mathrm{D}} = m_{\mathrm{D}}$ and $\tilde{m}_{\mathrm{E}} = m_{\mathrm{E}}$. This method serves as a comparison to determine an upper bound of what can be achieved.

2) Data Driven (Data): For this we determine user specific values using the training data set. Let $\hat{M}_{\mathrm{ID}}$ be the set of historical transactions for user m_{ID}. From this set we determine the



(a) Power fill-level forecast and realization

(b) Energy bounds forecast and realization

(c) ENS by transaction (sorted)

Fig. 3. Simulation results depicting the mean outcome over 100 runs for different approaches.

transaction duration (i.e., $m_{\mathrm{D}} - m_{\mathrm{A}}$) for all transactions in $\hat{M}_{\mathrm{ID}}$. Subsequently, we obtain the mean duration μ_{L} and standard deviation σ_{L} for the EV in question. Likewise, we obtain also the mean of energy supplied μ_{E} and standard deviation σ_{E} from the training set. Unknown transaction parameters are now obtained as follows:

$$\tilde{m}_{\mathrm{D}} = \min(m_{\mathrm{A}} + \mu_{\mathrm{L}} - \sigma_{\mathrm{L}}, T) \tag{13}$$

$$\tilde{m}_{\mathrm{E}} = \mu_{\mathrm{E}} + \sigma_{\mathrm{E}} \tag{14}$$

To be robust against errors, the energy requested is purposefully overestimated and the duration underestimated. The purpose of this paper is to present the framework and therefore a sophisticated data driven method is outside of the scope.

3) Smart Charging Default (Smart): The Netherlands currently adopts a default setting for smart charging [16] in which each EV will receive 30 kWh in 6 hours (360 one minute intervals): $\tilde{m}_{\mathrm{D}} = \min(m_{\mathrm{A}} + 360, T)$ and $\tilde{m}_{\mathrm{E}} = 30$ kWh.

4) First Come, First Serve (FCFS): Lastly we use for comparison the simple FCFS heuristic seen often in practice. For this, we sort Z_t according to the order of arrival m_{A}.

C. Simulation Results

Two different simulations are performed: one in which the proposed approach is used to find an appropriate fill-level $\tilde{\mathbf{x}}$; and a greedy approach, denoted by an asterisk (*), that fully utilizes the grid capacity (i.e. $\tilde{x}_t = \overline{x}, \forall t \in \mathcal{T}$) to enhance the QoS to users. For the former we use $\alpha = 1.1$ and $\beta = 0.9$ to provide robustness. A total of 100 simulations are performed for each prioritization approach, each with 250 randomly chosen transactions.

An overview of simulation results is presented in Table II, where the *min*, *mean*, and *max* columns provide the statistics of obtained results for the 100 simulation runs. As was expected, the methods that prioritize charging of individual EVs based on user specific information (*Perfect* and *Data*) clearly perform better in reducing grid load, increasing the self-consumption and raising the total energy served. Here, self-consumption is defined as the percentage of directly used solar energy ($\mathbf{x}_{\mathrm{B}}$):

$$\text{self-consumption} = \frac{\sum_{t \in \mathcal{T}} \min(x_{\mathrm{EV},t}, |x_{\mathrm{B},t}|)}{\sum_{t \in \mathcal{T}} |x_{\mathrm{B},t}|} \cdot 100\% \tag{15}$$

The self-consumption improves from 72.0% to 85.4% when comparing the often used *FCFS** to the proposed *Data*.

In Fig. 3a the power curves of the average of 100 simulation runs are shown. It is clearly visible how the overestimation for energy results in feed-in of PV energy at the end of the day as all EVs are either fully charged or have departed, but also how *Data* leads to reduced peaks when compared to *FCFS**. Fig. 3b shows an energy graph, where it can be observed how the realized profile deviates from the planning due to the forecast errors in the PV data. The final energy content at the end of the day is lower than the planned ($\tilde{\mathbf{x}}_{\mathrm{EV}}$) due to overestimation.

Similarly, we see better results when it comes to the energy not served (ENS) which is the energy not provided to the car in the simulation study compared to the the actual energy served in the real-world data, denoted by m_{S} (i.e., ENS $= m_{\mathrm{S}} - m_{\mathrm{E}}$). For the whole fleet, it can be observed that the average ENS, as percentage of the total originally demanded energy by the whole fleet, has improved in *Data* compared to *Smart* and *FCFS*. Similarly, the energy worst-case (WC) of energy not served to a single car for each of the simulations has also significantly improved. However, the performance of *Data* is still far from the results obtained for *Perfect*. The latter is able to attain the planned profile $\tilde{\mathbf{x}}$ without significant loss in QoS.

Lastly, we evaluate the fairness of the algorithm using Jain's fairness index [17], in which the fraction of provided energy compared to real-world served energy ($\frac{m_{\mathrm{E}}}{m_{\mathrm{S}}}$) is used as the throughput metric. Unexpectedly *Data* is outperformed by *Smart* in this metric. Further data analysis reveals that, although overall more energy is served (Fig. 3c), EVs suffering from ENS percentually receive less energy in *Data*. It is expected that this is caused by unpredictable EVs that depart much earlier than expected (e.g., because of a meeting elsewhere, whilst normally they stay the whole day). The resulting *Data* prioritization (with 8 or 9 hours in a working day) is then less favourable than the 6 hours with *Smart*.

For the greedy approaches, denoted by the asterisk (*), similar trends are observed. Here, more grid capacity is used to enhance the QoS, which leads to lower ENS, but also in a lower self-consumption rate. It is worth noticing that the *Data* approach achieves in general quite similar results as the often in practice employed *FCFS** approach.

TABLE II
NUMERICAL RESULTS OF THE PERFORMED SIMULATIONS WITH DIFFERENT ONLINE CONTROL METHODS

	Obj.val [MW]	**Energy Served** [kWh]			**Self-Consumption** [%]			**Average ENS** *(whole parking lot)* [%]			**Worst-Case ENS** *(single EV)* [kWh]			**Fairness Index [17]** [-]		
Case	mean	min	mean	max	min	mean	max	min	mean	max	min	mean	max	min	mean	max
Perfect	3260	5293	5892	6329	80.3	90.9	97.5	0.0	0.1	2.2	0.0	1.4	28.9	0.982	1.000	1.000
Data	4948	5051	5449	5739	77.0	85.4	91.6	2.7	7.5	12.0	15.5	38.0	60.6	0.891	0.933	0.964
Smart	5814	4830	5223	5610	75.0	81.3	88.4	7.7	11.3	15.7	31.2	45.2	58.5	0.938	0.959	0.978
FCFS	5858	4790	5176	5514	74.7	81.1	88.2	7.8	12.1	16.4	36.5	51.1	65.7	0.854	0.897	0.938
*Perfect**	7964	5293	5896	6470	64.4	72.1	79.4	0.0	0.0	0.0	0.0	0.0	0.0	1.000	1.000	1.000
*Data**	7975	5192	5728	6209	65.2	72.0	77.9	0.8	2.8	4.8	8.5	24.7	42.0	0.936	0.966	0.992
*Smart**	8099	5125	5577	6019	64.6	71.3	76.8	2.4	5.4	8.5	19.7	35.9	51.2	0.970	0.982	0.994
*FCFS**	7983	5028	5546	6001	66.0	72.0	77.8	3.1	5.9	8.6	26.4	42.4	65.4	0.924	0.948	0.969

V. CONCLUSION AND FUTURE WORK

This work presented a robust control framework for smart charging of large fleets of EVs in grid-constrained parking lots. The approach relies only on data generally available to a CPO, is scalable, does not depend on user interaction, and can be directly utilized in practice. Furthermore, it has been shown that, even with a simple prioritization strategy, significant improvements are achieved in both ENS reduction and self-consumption. Simulation results show that the self-consumption is improved from 72.0% (*FCFS**) to 85.4% (*Data*) when using the planning step. Alternatively, the ENS is reduced from 5.9% to 2.8% with *Data**. Hence, the presented solution enables further electrification of mobility in congested grids by better utilizing existing capacity.

In future work, we investigate more sophisticated methods to increase the accuracy of the estimated energy and departure time. Adding user input, such as an app or an *opt-out* option for incidental use, is also considered. It is expected that this leads to a more accurate prioritization and thus better performance. Lastly, the offline planning phase could be executed more often to incorporate actual data of active transactions. This allows for a more accurate fill-level estimation and use of the fleet flexibility for portfolio balancing.

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