Fairness-aware Management of Electric Vehicle Charging Stations

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***Abstract*— This paper presents an optimization framework for scheduling electric vehicle (EV) charging at public stations, with the aim of minimizing overall user dissatisfaction while taking into account arrival time, charging duration, and power demand. To promote fairness, the framework differentiates between high-priority users (those without access to home or workplace charging) and low-priority users (those with such access). In addition, it ensures contiguous charging time slots by incorporating trigger functions into the optimization model. The problem is formulated as a Mixed Integer Linear Program (MILP). The effectiveness of the proposed approach is demonstrated through simulations using EV charger data from the UC Merced campus parking lot.**

***Index Terms*— Electric vehicle charging scheduling, social equity awareness, Mixed Integer Linear Program**

I. INTRODUCTION

Transportation accounts for a significant share of global greenhouse gas emissions, making the widespread adoption of electric vehicles (EVs) essential for reducing the carbon footprint and combating climate change [1]. However, large-scale EV adoption faces critical challenges, including long charging times and extended queues at Fixed Charging Stations (FCSs), largely due to insufficient charging infrastructure [2]. According to [3], a Level 1 charger (120V) requires over 8 hours to provide approximately 75–80 miles of range, whereas a Level 2 charger (240V) takes about 4 hours, and a Level 3 charger (480V+) can deliver up to 90 miles of range in under an hour. Also, the rapid increase in EV ownership continues to outpace the deployment of FCSs, making it difficult for drivers to secure timely charging opportunities. This challenge is especially acute in disadvantaged communities, where charging stations remain scarce [4]. The lack of reliable infrastructure is a major barrier to EV adoption in these areas. Addressing this imbalance is critical to ensuring the benefits of electrification are accessible to all users. One promising solution is the development of scheduling systems that give preference to disadvantaged users who lack at-home charging.

A substantial body of literature has explored scheduling strategies aimed at improving user satisfaction and fairness at fixed charging stations (FCSs). For example, [5] and [6] developed optimization frameworks to minimize waiting time and operating costs jointly. Other works, such as [7], [8], have proposed power allocation strategies to ensure fair service among arriving EV customers. In addition, some studies have targeted carbon reduction objectives by optimizing charging and discharging times based on carbon intensity

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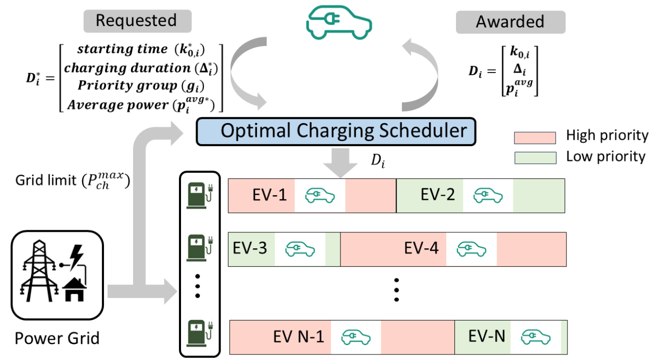

Fig. 1. Block diagram of the proposed fairness-aware management framework for EV charging stations. The system schedules charging sessions by considering user demands and technical constraints, while giving priority to high-priority users (those without access to home charging).

signals [9]. While these studies employ different definitions of fairness, this paper focuses specifically on fairness in accessing charging-station resources for disadvantaged users, who lack at-home charging.

Research that incorporates fairness indices with respect to disadvantaged communities has largely centered on FCS location optimization. For example, [10] and [11] conducted extensive studies on strategically planning EV charging infrastructure to prioritize underserved communities. Similarly, some efforts have explored deploying mobile charging stations (MCSs) to economically disadvantaged areas, thereby improving charging access for individuals without home or workplace charging options [12], [13]. However, these studies primarily focus on optimizing the placement of FCSs/MCSs with fairness considerations and give limited attention to scheduling strategies at individual stations. An exception is [12], who examined both fairness-aware deployment and scheduling strategies for MCSs. Yet, even in this case, the proposed scheduling approach may not guarantee contiguous charging time slots for EV users.

Although fairness-aware deployment and scheduling frameworks have been explored, an often-overlooked aspect is the provision of contiguous charging sessions. *A contiguous charging session is a session where the charging is performed without breaks or time interruptions.* Unlike fragmented schedules, contiguous time slots better reflect real-world charging behavior, improving user convenience. In much of the literature, this requirement is enforced through hard constraints. For example, [14] ensures that once an EV begins charging, it is disconnected only after reaching the requested charging duration or state of charge (SOC).

While effective in guaranteeing contiguous slots, such an approach may increase overall customer dissatisfaction, as fewer users are able to access charging. Other strategies involve coordinating across multiple FCSs by shifting reservations within the network—accommodating longer charging sessions at one station while redirecting shorter sessions to underutilized stations [15]. However, this solution is limited when neighboring FCSs are located too far for the incoming EV to reach.

Fig. 1 illustrates the overall architecture of the proposed methodology. The primary objective is to design an optimal scheduler that enables the fair utilization of EV charging stations. Each EV user is assumed to provide their desired charging profile, comprising arrival time, charging duration, and energy demand, before arriving at the station. The optimal scheduler determines when each user begins charging, how long the session lasts, and the amount of power the user receives from the charger. The optimization aims to minimize disparities in charging power, start time, and charging duration across users, while accounting for the power capacity and the limited number of charging ports available at the station. To promote fair access, the cost function includes weighting factors that prioritize high-priority (HP) users (those without access to home or workplace charging) over low-priority (LP) users (those with such access). Additionally, the scheduler enforces contiguity constraints to ensure that all charging sessions occur in uninterrupted time intervals.

This paper makes two main contributions. First, EV scheduling at an FCS is posed as an optimization problem to minimize overall user dissatisfaction among EV customers with respect to arrival time, charging duration, and power demand. To promote social fairness, the framework distinguishes between HP and LP users. The problem is formulated as a Mixed Integer Linear Program (MILP) [16] and can be efficiently solved using modern numerical solvers. Second, we ensure guarantees for contiguous charging time slots by incorporating trigger functions into the optimization framework. This novel approach provides contiguous allocations regardless of whether the customer's requested charging duration is fully met.

II. Preliminaries and problem statement

A. User groups

Let us consider $I = \{1, \ldots, N\}$ as the set of users visiting a charging station on a given day. The number of users can vary from day to day. We will treat N as a stochastic variable, sampled from the distribution $N \sim \mathcal{D}_N$. The user can belong to the group of HP users (e.g., students who do not have access to chargers at home or school) or LP users (e.g., office workers with access to fast charging at the workplace). This information is captured by the variable $g_i \in \Gamma = \{HP, LP\}$, where Γ is the list of user groups. In what follows, we consider g_i as a random variable sampled from the distribution $g_i \sim \mathcal{D}_g$. Based on the above information,

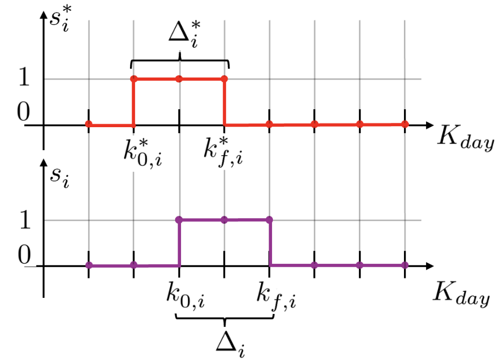

Fig. 2. Illustration of the charging indicator function $s_i[k]$. Note: $s_i[k] = 1$ indicates that the user can charge the vehicle during the time slot k. $s_i^*[k] = 1$ indicates that the user "requests" charging in the time slot k.

we can build the set of HP and LP users

$$I_{HP} = \{i \in I : \quad g_i = HP\} \tag{1}$$
$$I_{LP} = \{i \in I : \quad g_i = LP\} \tag{2}$$

Remark 1: In this paper, we assume the existence of a classifier $h : \theta_i \mapsto \Gamma$ that assigns each user $i \in I$ to a group Γ. The classifier operates on θ_i, which denotes the set of user characteristics, such as: (i) whether the user has access to charging at home; (ii) the typical commuting distance from home to the workplace or study location; and (iii) whether the user has access to convenient public transportation. We hypothesize that users without home charging, who must commute long distances and lack access to public transportation, should be classified as HP, whereas users residing in proximity to a charging station and with access to home charging should be classified as LP.

B. Time slots

The day is divided into discrete time slots (e.g., 30 minutes) denoted by $K_{day} = \{1, \ldots, N_K\}$, where N_K is the number of daily time slots. The user $i \in I$ would like to charge the vehicle at the beginning of time slot $k_{0,i}^*$, charge for duration Δ_i^*, and leave at $k_{f,i}^*$. Therefore, $\Delta_i^* = k_{f,i}^* - k_{0,i}^*$ (see Fig. 2). These times are uncertain and can be modeled via stochastic distributions given by $k_{0,i}^* \sim \mathcal{D}_k$, and $\Delta_i^* \sim \mathcal{D}_d$. We use the super-index * to refer to signals that the users desire. We define $s_i^*[k] \in \{0, 1\}$ as a boolean charging indicator that is "one" during the time slots that the user i would like to charge, and zero otherwise:

$$s_i^*[k] = \mathbb{1}_{[k_{0,i}^*, k_{f,i}^*]}[k] = \begin{cases} 1 & \text{if} \quad k \in [k_{0,i}^*, k_{f,i}^*] \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

In practice, the actual time slots available for the user to charge the vehicle may differ from the "desired" ones. We denote $s_i[k] \in \{0, 1\}$ as the actual charging indicator. The charging station has M charging ports, which can charge one electric vehicle at a time. This constraint can be modeled as:

$$n[k] := \sum_{i \in I} s_i[k] \leq M \quad \text{for all } k \in K_{day} \tag{4}$$

where $n[k]$ represents the EV users connected to charging ports in each time slot.

C. Power and Energy

The total charging energy requested by the user is given by

$$e_i^* = \sum_{k \in K_{day}} p_i^{avg*} s_i^*[k] \Delta T \quad (5)$$

where p_i^{avg*} is the desired average charging power requested by user i and ΔT is the time slot duration. We denote e_i as the actual total energy provided to the user i by the charging station. Let P_{ch}^{max} define the total power provided to the charging station by the grid. Then,

$$\sum_{i \in I} \left(p_i^{avg*} s_i[k] - \Delta p_i[k] \right) \leq P_{ch}^{max} \quad \forall\, k \in K_{day} \quad (6)$$

where $\Delta p_i[k] \geq 0$ is the loss of charging power. Here, Δp_i represents the difference between the desired power requested by an EV user and the actual power allocated from the charging ports at each time slot. Next, let P_{port}^{max} define the maximum power that can be delivered to EV from a single charging port. Then,

$$p_i^{avg*} s_i[k] - \Delta p_i[k] \leq P_{port}^{max} \quad \forall\, i \in I,\ k \in K_{day} \quad (7)$$

D. Problem Statement

Assumption 1: We assume that the following parameters are known: $\Delta T, \mathcal{D}_N, \mathcal{D}_g, \mathcal{D}_k, \mathcal{D}_d, M, P_{ch}^{max}$. We also assume that the EV customer will provide the information $D_i^* = [k_{0,i}^*, \Delta_i^*, g_i, p_i^{avg*}]$ to the FCS ahead of time to reserve the charging slot.

Problem 1: Given Assumption 1, we want to find the charging profiles for all the users, $s_i[k]$, where $i \in I$, during the time window $k \in K_{day}$ such that

- Difference between requested ($s_i^*[k]$) and actual charging slots ($s_i[k]$) is minimized for each user i.
- Difference between requested (e_i^*) and actual total energy (e_i) is minimized for each user i.
- HP users are given preference in accessing the charging time slots and energy requirements when compared to LP users.
- Physical capacity and power limits of the charging station are satisfied.

III. Time and Power Allocation

In this section, we present the optimization framework to solve Problem 1. To better quantify priorities in the allocation process, we introduce a "dissatisfaction" metric for time allocation that measures the (quadratic) difference between the request and the obtained time slots for charging. We evaluate these metrics for both HP and LP user groups:

$$s_{HP}^2 = \sum_{i \in I_{HP}} \sum_{k \in K_{day}} \frac{(s_i^*[k] - s_i[k])^2}{n_{I_{HP}}} \quad (8)$$

$$s_{LP}^2 = \sum_{i \in I_{LP}} \sum_{k \in K_{day}} \frac{(s_i^*[k] - s_i[k])^2}{n_{I_{LP}}} \quad (9)$$

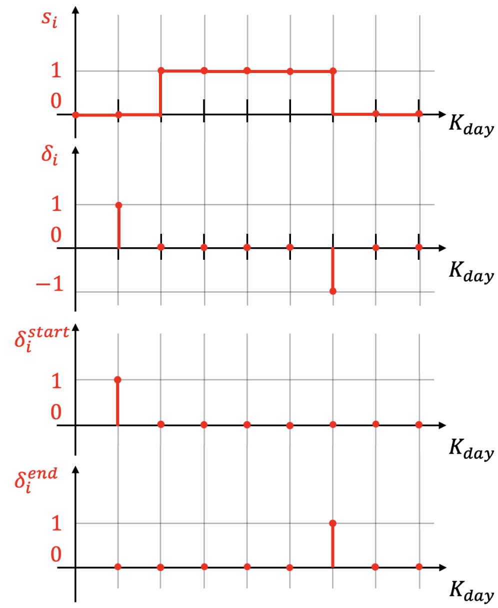

Fig. 3. Illustration of the trigger functions for start (δ_i^{start}) and end (δ_i^{end}) of charging, used in this work to enforce contiguous charging sessions.

Each metric is divided by the number of users in each group ($n_{I_{HP}}, n_{I_{LP}}$) in order to obtain an average dissatisfaction. If all the charging requests are fulfilled, then $s_{HP} = 0$ and $s_{LP} = 0$. We also introduce a user-defined weight $\theta_s \in [0, 1]$ to penalize the weighted dissatisfaction of all users:

$$\theta_s s_{HP}^2 + (1 - \theta_s) s_{LP}^2 \quad (10)$$

When $\theta_s \to 1$ we assign higher priority to HP users. It is the "tuning knob" that the operator of the EV charging station can use to give preference to HP users.

Next, we provide constraints for the energy allocation. To do so, we determine the total energy provided to each user as $e_i = \sum_{k \in K_{day}} p_i[k] \Delta T$. Now, similar to time allocation, we introduce a "dissatisfaction" metric for energy allocation that measures the average quadratic difference between the request and the obtained charging energy:

$$E_{HP}^2 = \sum_{i \in I_{HP}} \frac{(e_i^* - e_i)^2}{n_{I_{HP}}} \quad (11)$$

$$E_{LP}^2 = \sum_{i \in I_{LP}} \frac{(e_i^* - e_i)^2}{n_{I_{LP}}} \quad (12)$$

We also introduce a user-defined weight $\theta_E \in [0, 1]$ to penalize the weighted dissatisfaction between the HP and LP users as given below.

$$\theta_E E_{HP}^2 + (1 - \theta_E) E_{LP}^2 \quad (13)$$

The solution to the optimization of the charging strategy does not guarantee that $s_i[k]$ is contiguous. There may be cases where a user is asked to charge during non-consecutive time windows, which is not practical for the user. To address this issue, we introduce the indicator function:

$$\delta_i[k] = s_i[k+1] - s_i[k] \quad (14)$$

This function is equal to $+1$ during the time slot before the user i starts to charge. It is -1 when the time slot before the user leaves the charging station (see Fig. 3). Our idea is to introduce "triggers" in the above function to signal the start and end of the charging of the vehicle.

$$\delta_i[k] = \delta_i^{start}[k] - \delta_i^{end}[k] \tag{15}$$

where $\delta_i^{start}[k] \in \{0,1\}$ is a "boolean" trigger function that is active during the time instant preceding the start of the charging and $\delta_i^{end}[k] \in \{0,1\}$ generates a pulse before the end of the charging session. The indicator function is governed by the following difference equation

$$s_i[k+1] = s_i[k] + \delta_i^{start}[k] - \delta_i^{end}[k] \tag{16}$$

With this notation, it is straightforward to guarantee that the user is allocated consecutive time windows.

Proposition 1: A charging profile is *contiguous* during the period $k \in K_{day} = [1, N_K]$ if it has a single non-zero start trigger and a single non-zero end trigger. Mathematically, this means

$$\sum_{k \in K_{day}} \delta_i^{start}[k] = 1, \qquad \sum_{k \in K_{day}} \delta_i^{end}[k] = 1 \tag{17}$$

Proof: The proof is straightforward as it makes use of the fact that δ_i^{start} and δ_i^{end} are boolean functions. The constraints given by (17) ensure that there is only one start time and one end time per user on the given day. ■

Remark 2: The contiguity constraint enforced using (16) and (17) leads to better quality of service, which further reduces the dissatisfaction of the users of the EV charging station.

Our goal is to minimize the overall dissatisfaction $(s_{HP}^2, s_{LP}^2, E_{HP}^2, E_{LP}^2)$ among the two groups. It can be fulfilled by solving the following optimization problem:

$$\begin{aligned}
\mathbb{P}: \min_{s_i, \delta_i^{start}, \delta_i^{end}, \Delta p_i} \quad & \alpha\left(\theta_s s_{HP}^2 + (1-\theta_s) s_{LP}^2\right) + \\
& (1-\alpha)\left(\theta_E E_{HP}^2 + (1-\theta_E) E_{LP}^2\right) && \text{(18a)}\\
\text{s.t.} \quad & (4), (6), (7), (16), (17) && \text{(18b)}\\
& 0 \le \Delta p_i[k] \le p_i^{avg*} s_i[k] && \text{(18c)}\\
& \delta_i^{start}[k], \delta_i^{end}[k], s_i[k] \in \{0,1\} && \text{(18d)}\\
& i \in I,\ k \in K_{day} && \text{(18e)}
\end{aligned}$$

Here, α is a user-defined weight to penalize the dissatisfaction between time and energy allocation. The above optimization problem is an MILP. In (18c), a value of $\Delta p_i[k] = 0$ indicates that the user's desired charging power is fully satisfied by the station for time slot k, whereas $\Delta p_i[k] = p_i^{\text{avg}*}$ implies that no charging power is delivered to that user during the k^{th} time slot.

IV. Numerical Simulations

A. Case Study

The simulations were conducted using EV charging data collected from the UC Merced campus parking lot (Bellevue Lot) during the Spring 2025 semester. This data was provided by the University of California, Merced Transportation and Parking Services. The entire dataset is characterized as

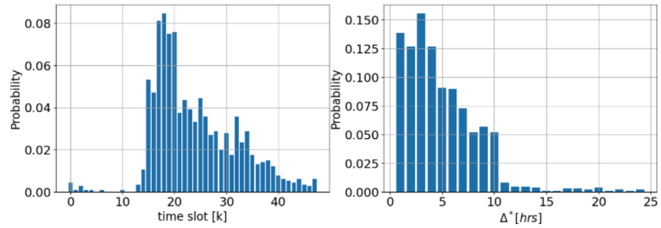

Fig. 4. (Left) Probability distribution ($\mathcal{D}_k$) of desired arrival time ($k_{0,i}^*$) and (Right) probability distribution ($\mathcal{D}_d$) of desired charging duration (Δ_i^*).

$$\mathcal{Z} = \{(k_{0,j}^*, \Delta_j^*, p_j^{avg}, day_j)\}_{j=1}^{N_{session}} \tag{19}$$

where j is the charging session index[1], day_j is the day of the session, and $N_{session} = 1342$ is the total number of charging sessions recorded by the charging station during the Spring semester of 2025. We divided each day into $N_K = 48$ half-hour time slots. The dataset $\mathcal{Z}$ was used to construct the empirical probability distributions $\mathcal{D}_k(\mathcal{Z}), \mathcal{D}_d(\mathcal{Z})$. Fig. 4 shows the histograms of these variables. One can observe that most users arrive between $k = 14$ (7 am) and $k = 22$ (11 am); their arrival rate slowly decreases during the day. It is also uncommon to see charging sessions between midnight and 6 am ($k = 0$ to $k = 12$). The histogram for charging duration shows that 40% of the charging sessions require less than 5 hours. It is also observed from the data that the average charging power requested by the users is 6 kW, with a maximum value of 12 kW.

The collected dataset does not contain the priority of each user, g_j. To overcome this lack of information, we assume that g_j is a random variable that follows a Bernoulli distribution ($\mathcal{D}_g$), where $g_j = 1$ indicates a HP user and $g_j = 0$ indicates a LP user. We assumed that 70% of the users are HP in this study; note that most of the users of the chargers at UC Merced are students, who often live in affordable apartments without access to EV chargers. Although the number of customers arriving per day is inherently stochastic ($N \sim \mathcal{D}_N$), it often fluctuates widely, with many days showing too few arrivals for meaningful simulation. Therefore, for simulation, the number of daily customers was fixed at $N = 15$.

The total number of ports available in the charging station is 20. However, since the current utilization ratio of existing chargers is relatively low, we artificially set the number of available ports to $M = 3$ to understand the behavior of our algorithm when the charging demand exceeds the available charging offer. The total charging power of the station is not known to the authors. We assume $P_{ch}^{max} = 15$ kW, which allows us to evaluate our algorithm under severe power limitations.

[1]We employ sub-index j to denote the charging session in the dataset $\mathcal{Z}$. The sub-index i is related to the user index in the day-to-day scheduler $\mathbb{P}$.

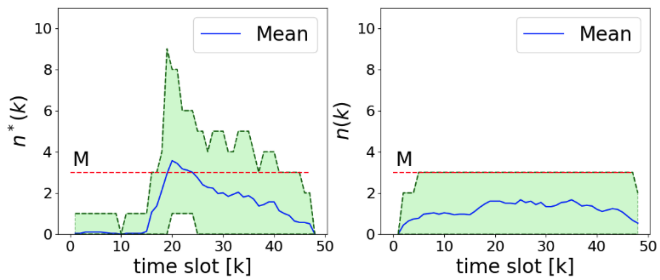

Fig. 5. Charging time-slot profiles of EV customers across the 30 days, showing the maximum, minimum, and mean number of arriving customers per slot. (Left) Requested charging time-slot profile ($n^*[k]$) and (Right) optimized ($\mathbb{P}$) charging time slot profile ($n[k]$).

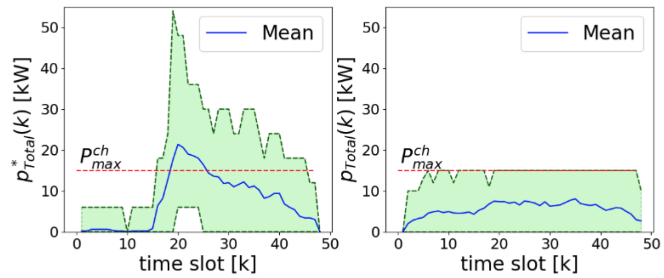

Fig. 6. Power profiles of EV customers across the 30 days, showing the maximum, minimum, and average power demand per slot. (Left) Requested power profile denoted by p^*_{total} and (Right) awarded (via $\mathbb{P}$) power profile denoted by p_{total} in kW.

B. Simulation and Discussion

We first generated the requests D_i^* for 15 EV customers per day over a period of 30 days. These requests are characterized by a tuple $D_i^* = (k_{0,i}^*, \Delta_i^*, g_i, p_i^{avg*})$, with $k_{0,i}^* \sim \mathcal{D}_k(\mathcal{Z})$, $\Delta_i^* \sim \mathcal{D}_d(\mathcal{Z})$, $g_i \sim \mathcal{D}_g$ and $p_i^{avg*} = p^{avg*}(\mathcal{Z}) = 6$kW. The charging schedule was computed via $\mathbb{P}$. The parameters θ_s and θ_E were both set to 0.7, thereby prioritizing HP users relative to LP users. We also set $\alpha = 0.5$ to assign equal priority to charging time-slot allocation and energy demand.

Fig. 5 illustrates the charging time-slot profiles of EV customers across the 30 days, showing the maximum, minimum, and average number of arriving customers per slot. As observed, the number of users frequently exceeds the charging port limitation (M) of the station, whereas the optimization-based scheduling ($\mathbb{P}$) ensures that this constraint is satisfied by distributing peak arrivals more evenly throughout the day. Similarly, Fig. 6 depicts the power demand profiles of EV customers across the same period, reporting the maximum, minimum, and average power demand (in kW) of arriving customers per slot. In this case as well, the requested power demands often exceed the per-slot maximum power limit ($P_{ch}^{\max}$) of the charging station, while the optimization-based scheduling $\mathbb{P}$ guarantees that the total power remains within this limit (e.g., by shifting users to an earlier or later time slot). The scheduler $\mathbb{P}$ also enforces the contiguity constraint.

Fig. 7 illustrates the charging time-slot profiles of 15 EV customers for a single day, with $\mathbb{P}$ and $\tilde{\mathbb{P}}$ (a modified version of the scheduler without the contiguity constraint (17)). One can observe that the scheduling generated by $\tilde{\mathbb{P}}$ splits the charging session into multiple (non-contiguous) time slots during the day, which is not practical for the users. This would require returning to the charging station multiple times per day. On the other hand, the proposed scheduler ($\mathbb{P}$) prevents that issue from occurring in practice, enforcing non-interrupted charging sessions.

Fig. 8 presents a sensitivity analysis of the optimal scheduling solution with respect to the weights θ_s and θ_E. The top row corresponds to the case $\theta_s = \theta_E = 0.9$, which strongly prioritizes HP customers over LP customers. In the plot concerning arrival time ($k_{0,i}$), most HP customers (blue dots) lie close to the diagonal line, while LP customers

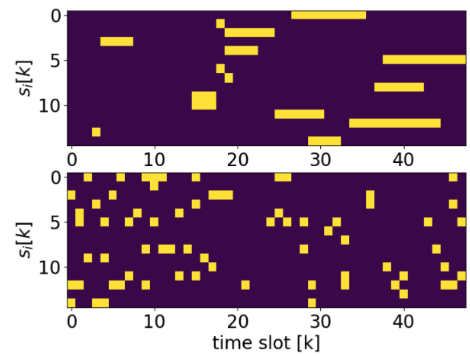

Fig. 7. Charging time-slot profiles of 15 EV customers for a single day; yellow blocks illustrate EV station usage ($s_i[k] = 1$). (Top) Time allocation computed via $\mathbb{P}$ (Bottom) time allocation obtained with $\tilde{\mathbb{P}}$, which does not enforce contiguity of charging time slots.

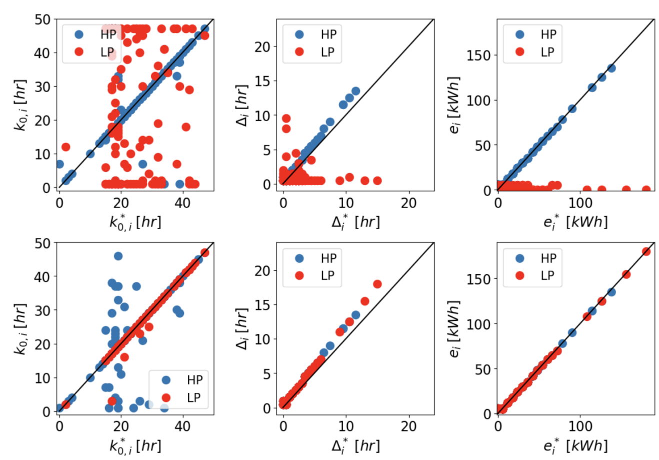

Fig. 8. The top row presents results when $\theta_s = \theta_E = 0.9$ and the bottom row presents results for $\theta_s = \theta_E = 0.5$. The plots in the leftmost column show the requested and awarded start time of charging, plots in the middle column show the requested and awarded duration of charging, and, in the rightmost column, plots show the requested and awarded energy.

(red dots) are more scattered. This indicates that for HP customers, $k_{0,i}^* \approx k_{0,i}$, meaning that their requested arrival times were either satisfied or closely matched. Similar trends can be observed in the plots for charging duration (Δ_i) and awarded energy (e_i). By contrast, the bottom row corresponds to $\theta_s = \theta_E = 0.5$, where HP and LP customers are treated with nearly equal priority. In these plots, both

HP and LP customers are distributed around the diagonal line in approximately equal proportion, except in the case of arrival time ($k_{0,i}$). Here, HP customers appear slightly more scattered than LP customers. This occurs because, although an equal fraction of HP and LP customers align with the diagonal, the HP population is substantially larger, and thus some HP customers cannot be assigned their requested start times. The effect of θ_s and θ_E on the solution of MILP can also be inferred from Table I.

TABLE I
SENSITIVITY OF $\mathbb{P}$ WITH RESPECT TO θ_s AND θ_E

α	$\theta_s = \theta_E$	$\sqrt{s^2_{HP}}$ Hr	$\sqrt{s^2_{LP}}$ Hr	$\sqrt{E^2_{HP}}$ kWh	$\sqrt{E^2_{LP}}$ kWh
0.5	0.1	2.125	2.111	0.641	0.54
0.5	0.5	3.422	3.415	0.694	0.645
0.5	0.9	2.741	2.89	0.55	0.577

A comparison of computation times of $\mathbb{P}$ with respect to N is provided in Table II. In terms of scalability, the MILP-based optimal scheduler ($\mathbb{P}$) can generate a solution within 2.34 minutes for 30 days of charging time-slot scheduling when $N = 24$.[2] However, when N is increased to 32 customers per day, the solution time exceeds 5 hours, and this value continues to grow nonlinearly as N increases further. A practical approach to alleviate this computational burden is to partition the daily customer set into smaller batches (e.g., morning and evening groups) and solve the MILP independently for each batch. Another option consists of reducing the number of time slots per day (N_K).

TABLE II
COMPUTATION TIME (t_{cpu}) FOR $\mathbb{P}$

N	# variables	t_{cpu} [30 days]	Avg. t_{cpu} per day
8	1536	9.76 sec	0.97 sec
16	3072	38.46 sec	3.85 sec
24	4608	2.34 min	14.06 sec
32	6144	$>$ 5 hrs	–

V. CONCLUSION

We proposed an optimization-based scheduling framework for EV charging stations that goes beyond simply fulfilling power and time demands. Our formulation enables site operators to assign differentiated priorities across user groups—for example, granting preference to EV users without access to at-home charging. To ensure interruption-free charging sessions, we introduced new trigger functions and formulated the overall scheduling problem as an MILP, which can be solved using state-of-the-art optimization solvers. The proposed scheduling strategy was validated using realistic charging data collected from the UC Merced campus parking lot. The results demonstrate the framework's ability to effectively redistribute charging slot allocations, while respecting the physical constraints of the charging infrastructure, offering interruption-free charging sessions, and supporting priority-based differentiation among user groups. Future work will tackle the experimental validation of the schedule and investigate the acceptance of the scheduler among users.

[2]We perform all the simulations using Python 3.19 on a Dell computer with 32 GB of Random Access Memory (RAM) and an Intel(R) i9-13900HX processor (2.20 GHz). We use Gurobi 12.0 as our optimization toolbox.

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