Cost-Minimizing EV Charging Scheduling under Power Constraints

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***Abstract*— As electric vehicle (EV) adoption surges, the power grid faces growing challenges from increased charging demands. Unregulated charging can strain the grid, underscoring the need for an intelligent power allocation strategy. This paper presents a proactive solution, utilizing historical data to forecast future charging demands and strategically deciding which vehicles to charge. Our approach aims to optimize charging across all vehicles while reducing associated costs. Empirical results validate the efficacy of our strategy: not only does it ensure all EVs reach their specified charge levels, but it also manages to do so more cost-effectively, resulting in a saving of at least 1% when compared to conventional methods.**

Keywords—Cost minimization, electric vehicle charging, scheduling algorithm.

I. Introduction

As the world shifts towards an eco-friendly paradigm, the automotive industry is transitioning to electric vehicles (EVs) powered by electric energy. With the growing prevalence of EVs, Information and Communication Technology (ICT) related to them has become a focal point of discussion. A significant challenge in this domain is optimizing the charging process to minimize costs and achieve desired battery levels.

One approach, as described in [1], employs deep reinforcement learning to determine which vehicle to charge. While effective, this method faces challenges in designing a reward function that balances cost and the desired State of Charge (SoC) of the battery. As the scale of vehicles increases, the experiment with numerous episodes becomes time-consuming. Conversely, the method in [2] bases charging decisions on the individual information of each vehicle and the available power. This strategy can be implemented without extensive data collection. However, it occasionally results in overcharging during peak times or fails to attain the target SoC.

To address these issues, our study introduces algorithms that promote low-cost charging during the vehicle's stay time and leverage previously collected EV patterns to forecast future demand. Our aim is to ensure all vehicles reach their target battery levels while keeping the total charging cost to a minimum. Through simulations, the proposed method demonstrated that all vehicles achieved the target energy level with a cost reduction of at least 1% compared to the existing method [2].

II. System Model

A. Scenario

Consider a scenario where we have K electric vehicles (EVs) denoted by a set of indices $EV=\{1,2,...,K\}$. Each of these EVs corresponds to an on-off charging station that can be coordinated by a Charge Point Operator (CPO). Upon the arrival of an EV and its subsequent connection to a charging station, data from the EV is transmitted to the CPO.

Before the onset of the next time slot, the CPO decides whether to charge a particular vehicle. This decision is based on data obtained from all plugged-in EVs, current available power, and the associated charging costs. The CPO then dispatches on-off signals to the respective stations for each time slot.

Each hour is divided into N_{slot} time slots, culminating in a total of 24 N_{slot} time slots in a day. These can be represented by a set of time slot indices $T=\{1,2,...,24N_{\text{slot}}\}$. The charging cost varies according to the Time-of-Use (TOU) rates, which are categorized into on-peak, mid-peak, and off-peak periods.

B. Notation

- $n_k^{\text{req}}(t)$: Number of required time slots to reach the target SoC level of k-th EV at time slot t.
- $n_k^{\text{soj}}(t)$: Number of sojourn time slots, or the duration of stay, for the k-th EV at time slot t.
- $n^{\text{lim}}(t)$: Maximum number of EVs that can be charged at time slot t.
- $V^{\text{urg}}(t)$: Set of EVs for which $n_k^{\text{soj}}(t) - n_k^{\text{req}}(t) \leq 0$. This set includes EVs that have an urgent charging need at time slot t.
- $V^{\text{norm}}(t)$: Set of EVs for which $n_k^{\text{soj}}(t) - n_k^{\text{req}}(t) > 0$. These EVs have a normal or non-urgent charging requirement at time slot t.

- $V^{\mathrm{sch}}(t)$: Set of EVs scheduled to be charged at time slot t.

III. Proposed Scheduling

The proposed scheme is outlined as follows:

1. Initial Analysis:

- Identify EVs that have not yet reached their target SoC level at the time slot t among the currently stationed EVs.
- For each of these EVs, compute $n_k^{\mathrm{req}}(t)$ and $n_k^{\mathrm{soj}}(t)$ as defined earlier.
- Evaluate the difference, $n_k^{\mathrm{soj}}(t) - n_k^{\mathrm{req}}(t)$, and arrange the EVs in ascending order based on this value.

2. Urgent Charging Assessment:

- If $n_k^{\mathrm{soj}}(t) - n_k^{\mathrm{req}}(t)$ is less than 1, the respective EV is added to $\mathrm{V}^{\mathrm{urg}}(t)$ in the given order; otherwise, it is added to $V^{\mathrm{norm}}(t)$.
- EVs in $V^{\mathrm{urg}}(t)$ have little to no discretion in their charging choice due to their impending departure or immediate charging needs. Consequently, they should be prioritized in $V^{\mathrm{sch}}(t)$, but not exceeding $n^{\mathrm{lim}}(t)$.

3. Non-Urgent Charging Assessment:

- In off-peak times, all necessary EVs are added to $V^{\mathrm{sch}}(t)$ sequentially, subject to availability.
- For mid-peak and on-peak times, the algorithm determines the number of each TOU time slot an EV has remaining until departure, comparing it with $n_k^{\mathrm{req}}(t)$. Depending on the sufficiency of available time slots in relation to the required slots, the algorithm decides the charging status of the EV.

Example: If $n_k^{\mathrm{req}}(t)$ is 5, and an EV has slots distributed as 3 off-peak, 3 mid-peak, and 2 on-peak until departure, the charging decision for an on-peak slot t would be negative. However, for a mid-peak slot t, the EV would be scheduled for charging.

4. Adaptation Under Power Constraints:

The initial algorithm assumes an always-available charging option for all EVs. In reality, under stringent power constraints, this assumption can lead to unsatisfactory outcomes. Therefore, during mid-peak slots, the system:

- Uses historical EV and power data to predict incoming EVs.
- Runs a virtual simulation based on the main algorithm.
- Identifies EVs that either fail to meet the target SoC or are overcharged during on-peak times.
- Determines the time slots when such EVs were deprioritized during off-peak charging.
- Schedules these EVs for charging during this mid-peak slot by adding them to $V^{\mathrm{sch}}(t)$.

This augmented strategy ensures optimal scheduling during mid-peak times, thereby reducing off-peak demand and enabling the power grid to manage potential capacity shortages more effectively.

IV. Simulation Results

Table 1 presents the parameters adopted for our case studies. We set $N_{\mathrm{slot}} = 4$, with the number of EV arrivals within a day and the load power profile being drawn from reference [2]. The notation $N(a, b^2)$ represents a normal (or Gaussian) distribution with a mean of a and a standard deviation of b.

TABLE I. Simulation Parameter Setting.

Parameters	*Values*
Total number of EVs	1000
Total days	3
EV battery capacity	58 kWh
EV charging rate	7kWh
SoC at the arrival	$N(0.5, 0.2^2)$
Sojourn time slots	$N_{slot} \times N(13, 3.8^2)$

Table 2 displays the TOU electricity pricing.

TABLE II. Time-of-Use Electricity Prices.

TOU	*Time*	*Price*
On-peak	11:00 ~ 12:00 13:00 ~ 18:00	168.5(₩/kWh)
Mid-peak	08:00 ~ 11:00 12:00 ~ 13:00 18:00 ~ 22:00	115.5(₩/kWh)
Off-peak	22:00 ~ 08:00	57.3(₩/kWh)

Table 3 provides a comparative simulation outcome over a span of three days using both the proposed method and the method from [2], based on the parameters specified.

TABLE III. Comparison of Charging Costs.

Power capacity	*Algorithm*	*Total cost*	*Unsatisfied EV*
5400kWh	[2]	4145272.76	532
	Proposed	4167180.21	0
5500kWh	[2]	4081761.3	0
	Proposed	4033457.68	0

For a power capacity of 5400kWh, the total cost incurred by the proposed algorithm closely aligns with that of [2]. However, the proposed approach notably reduces the number of unsatisfied EVs when compared to [2]. When the power capacity is increased to 5500kWh, both methods do not have unsatisfied EVs. Yet, the total cost under the proposed algorithm is reduced by 1% compared to [2].

V. Conclusions

In this paper, we introduced an algorithm tailored for minimizing charging costs under ideal conditions, as well as an extended approach that considers both EV patterns and power capacity. This enhancement was designed to address the limitations inherent to minimal-cost algorithms. Our simulation results demonstrate that, compared to pre-existing methods, our proposed solution can maintain or even reduce the overall charging costs while simultaneously improving the number of vehicles charged to their target SoC levels.

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