Distributed Approach for Temporal–Spatial Charging Coordination of Plug-in Electric Taxi Fleet

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***Abstract*—This paper considers a city with a large fleet of plug-in electric taxis (PETs) and studies the charging coordination problem of the fleet. The goal is to reduce charging cost for each PET, defined as the loss of service income caused by charging, by wisely choosing when and where to charge. Considering the fact that the fleet can contain thousands of autonomous PETs, this problem is approached in a distributed way. In detail, a two-stage decision process is designed for each PET in an online fashion upon receiving real-time information. In the first stage, a thresholding method is proposed to assist a PET driver in choosing a proper time slot for charging, with comprehensive consideration of state of charge of PET, time varying income, and queuing status at charging stations (CSs). In the second stage, a game-theoretical approach is devised for PETs to select CSs, so that the traveling and queuing time of each PET can be reduced with fairness. Extensive numerical simulations illustrate the following threefold benefits of the proposed approach: it can effectively reduce the charging cost for PETs, enhance the utilization ratio for CSs, and also flatten the unevenness of charging request for power grid.**

***Index Terms*—Backward induction, game-theoretical approach, plug-in electric taxi (PET), spatial selection, temporal scheduling.**

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NOMENCLATURE

Parameters and variables for temporal scheduling

T	Time horizon.
t, τ	Time slot indices.
Δ	Time length per slot.
Q	Full SOC capacity.
Q_l	Minimum SOC to travel to charging station.
$q(t)$	SOC level.
$L(t)$	Remaining operating time.
R_c, R_d	Charging and consuming power.
$x(t)$	Binary charging decision.
$\bar{\chi}(t)$	Average traveling time to charging station.
$\bar{\lambda}(t)$	Average queuing time at charging station.
$\gamma(t)$	Charging time to a full battery.
$c(t)$	Normalized charging cost.
$g(\tau)$	Average income.
$f(t)$	Threshold denoting expect future charging cost.
$\alpha(t)$	Probability of charging.
$\tilde{c}(t)$	Conditionally expected charging cost.

Parameters and variables for spatial selection

i, l, k	Indices of PETs to be charged.
$\mathbb{I}$	Set of PETs to be charged.
$\mathbb{B}$	Set of PETs influenced by other PETs.
$\mathbb{U}$	Stable set of PETs, $\mathbb{U} \in \mathbb{I}$.
j	Charging station index.
$\mathbb{J}$	Set of candidate CSs.
s_i	Strategy of PET i on CS selection.
s_{-i}	Other PETs' strategy except PET i.
$\vec{s}$	Strategy profile of PETs in $\mathbb{I}$.
$\mathbb{S}$	Strategy space of PETs.
χ_i^j	Traveling time of PET i to CS j.
λ_i^j	Queuing time of PET i at CS j.
p_i^j	Total time cost of PET i selecting CS j.

I. INTRODUCTION

A. Motivation and Related Works

THE ever increasing number of fuel-engined vehicles has caused many worldwide concerns, such as greenhouse gas emissions and fossil energy shortage [1]. Due to environmental advantages, electric vehicles (EVs) are widely recognized as a promising substitute. In recent years, EVs have been vigorously promoted all over the world, and expected to surge in the near future [2]. The potential large-scale integration of EVs has attracted much attention from academia in recent years [3]–[9]. From the perspective of power system operation, major concerns arise from the long charging time and large charging load of EVs. Without proper coordination, not only do they pose serious threat to power grids because of introducing load spikes [5], [10], [11], but also cause long queuing time of EVs at charging stations (CSs), leading to significant efficiency degradation of the EV operation [8]. Therefore, advanced EV charging coordination mechanisms are in urgent needs.

There has already been a large body of literature on coordinating the charging decision of EVs [12]–[19]. Rotering and Ilic [14] proposed two algorithms to address the scheduling of EVs that provide the economically optimal solution for EV owners based on a forecast of future electricity prices. He *et al.* [17] proposed optimal scheduling schemes, in which the charging rates are optimized to minimize the total cost of all EVs that perform charging and discharging during the day. Xiong *et al.* [20] investigated the optimal charging strategies of EVs based on drivers' self-interested charging behavior, traffic pattern, operating expense of CSs, and pricing.

However, the above-mentioned works mainly consider household plug-in EVs, which tend to charge at relatively fixed time slots and locations [17]. In other words, the selection of charging time and location would not be a major issue for household plug-in EVs, but the charging power is the critical variable and must be carefully optimized to satisfy the state of charge (SOC) requirement of EVs or load shift of grid. In contrast with the large literature on the charging coordination of household plug-in EVs, plug-in electric taxis (PETs) that account for a huge proportion of urban commercial EVs are less noticed.

In fact, a PET can run 10–20 times more mileage than a household EV per day and demand much more electricity, whereas the available charging period of a PET may be 5–7 times shorter due to its nonstop service. Therefore, in theory, a PET may account for 50–140 household EVs in terms of average charging power. For example, the city of Shenzhen in China now has 10 000 PETs in operation, which is equivalent to at least 0.5 million household EVs in terms of average charging power, which can bring significant impact to the grid. As an important role in the future power system, PETs are attracting more and more attention from the community. Early studies investigate the infrastructure planning problem of a PET system, such as for New York City [21] and Vienna city [22]. Wang *et al.* [23] optimized the deployment of battery swapping stations for EV taxis, with the help of data analytics of taxi routes, battery swapping demand profile, and the driving time.

Meanwhile, as the charging time and location are less predictable than household EVs, a PET fleet can bring strong unpredictable peak load to the grid. Albeit existing research works, such as [24]–[26], are able to characterize and analyze charging loads of PETs in both temporal and spatial domains, it remains an issue with highly random EV charging that may incur spikes in load profiles. Therefore, coordinating the charging of PET fleet is very critical to the power system. However, the coordination methods designed for household EVs cannot be directly applied to PET fleet because there are two types of problems. The destination and route of PET are determined by the passengers, thus they are unknown and unpredictable to the driver. Therefore, it becomes very challenging for the driver to decide when and where to charge under this randomness. On the other hand, since PETs typically prefer fast charging to save time, there is little room for optimization of their charging rates. Consequently, there are pressing demands on design specific methods for the coordination of PETs, which motivates this paper.

The existing charging coordination mechanisms of PETs can be summarized into two categories: temporal scheduling and spatial selection. The temporal scheduling aims to decide suitable charging time slots for PETs, for example, Yang *et al.* [27], [28] studied the optimal charging scheduling problem to maximize the operating profit of PETs by making a temporal schedule under uncertain electricity prices and time-varying incomes. The spatial selection instead aims to locate geodistributed CSs for PETs to lower their charging expense. For example, Zhou *et al.* [29] investigated the optimal spatial selection of PETs based on the differences of charging prices, queuing time, and distance among different CSs. Tian *et al.* [30] designed a real-time CS recommendation system for PETs by combining each EV taxi's historical recharging events and real-time GPS trajectories. The recommendations can significantly reduce the total waiting time and increase working time and revenue. Lu *et al.* [31] proposed a dispatching strategy with charging plans to lower the waiting time of recharging and thus increase the workable hours for taxi drivers.

However, previous studies may suffer from three main drawbacks. First, the coordination of PET fleet charging requires joint efforts from both temporal and spatial domains, which is computationally difficult in general and has not been properly addressed yet. Second, many studies assume a central controller to make decisions for the entire fleet and optimize the social welfare; however, as the fleet is made up of autonomous and self-interested PETs, a distributed decision-making scheme is more practical. Third, most methods are developed based on electricity price variations, which in practice may not be frequent and aggressive enough to affect the charging behavior of PETs. In contrast, PETs are more sensitive to queuing time because unwisely waiting in a long queue can waste hours, thus shortening service time and losing revenue. Therefore, electricity prices are not considered here to highlight the importance of queuing time. In fact, slight modification on the formulation of charging cost (4) can take electricity prices into account and will not affect the performance of the proposed algorithms.

Based on the critical information of queuing time, this paper solves the temporal and spatial coordination problems together in a fully distributed way for each PET. As a result, the proposed scheme can effectively reduce the queuing time of PETs, enhance the utilization ratio for CSs, and also flatten the unevenness of charging request for the power grid.

B. Our Work

In this paper, we consider a city-wide PET charging system that consists of a sufficient number of CSs, a fleet of the same type of PETs, and an information center, which can gather

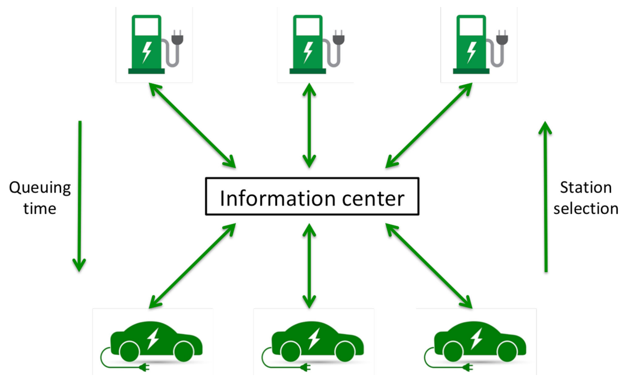

Fig. 1. Information flow diagram.

critical information of both PETs and CSs, including PET locations, charging requests, and CS queuing status. The information center will also broadcast the queuing status of CSs to PETs, which will assist them to wisely decide when and where to charge. A smart device is assumed to be installed on each PET for communication and computation. The diagram of information flow is displayed in Fig. 1.

One major obstacle to the temporal–spatial coordination of PET charging lies in the uncertainty of PETs' exact future positions. Unlike household EVs and buses, the routes of PETs are determined by passengers and highly random. Therefore, the spatial selection of charging cannot be made in advance since the future locations of PETs are unknown. To cope with this difficulty, we propose a two-stage decision mechanism for each PET, i.e., first decide the charging slot, and then at the charging slot select a CS from the nearby ones. The contributions of this paper can be summarized as follows.

1) For each PET in the fleet, a distributed online coordination mechanism is proposed that consists of two stages: the temporal scheduling stage and the spatial selection stage.
2) The temporal scheduling problem is solved by a computation-efficient thresholding method, which considers the queuing time as the most critical information, instead of electricity prices.
3) The spatial selection problem is tackled by a game-theoretic approach, which converges quickly to a Nash equilibrium (NE) that ensures the fairness of PETs.

By applying the proposed approach, three major benefits can be offered to PETs, CSs, and power grid, as to be shown by numerical results. First, the queuing time as well as the charging cost is reduced for PETs; second, the utilization ratio is enhanced for CSs; and third, the unevenness of charging requests is flattened for a power grid. The remainder of this paper is organized as follows. In Section II, we present the formulation and solution of the temporal scheduling problem, whereas the spatial selection problem is elaborated in Section III. Extensive numerical results are illustrated in Section IV, followed by conclusions drawn in Section V.

II. Temporal Scheduling Problem

The charging coordination of PETs naturally consists of temporal and spatial aspects. However, as discussed above, most, if not all, related works have only focused on one aspect. The key challenge is that it is almost intractable to comprehensively address the problem in a practical online setting, considering a great number of future uncertainties, e.g., the starting points and destinations of passengers. Therefore, we design a two-stage decision process to model both the individual behavior of PETs and their interactions, such that the temporal–spatial coordination can be decoupled and, more importantly, implemented in a distributed fashion. In the prior stage of temporal scheduling, each single PET simply decides which time slot to charge. Since other PETs' decisions are temporarily unknown, it is neither necessary nor practical to take into account explicit spatial attributes of variables. This two-stage scheme will significantly relieve the computational efforts, making itself more applicable to real scenarios.

In this section, we focus on tackling the temporal scheduling problem for each PET in the fleet, with the aim to minimize its charging cost defined as the potential loss of service income. Then, this problem is turned into choosing the charging slot with short queue length and low income. Note that the charging slot is determined in an online fashion. That is, upon receiving the current queuing status of CSs, a PET needs to decide starting charging now or waiting for future opportunities. At last, an efficient thresholding method is proposed to solve the above-mentioned problem, which essentially compares current charging cost and the expectation of future cost.

A. Scenario Description

For simplicity, we assume that the PETs are of the same type and running all the day except for charging periods. We also assume that every charge is a full effort, which is often a good decision in practice, because splitting a full effort will significantly increase an EV's charging frequency and thus traveling time to and from CSs. We consider a long time horizon of T time slots. Let $q(t)$ be the SOC level at (the beginning of) slot $t, t \in \{1, 2, 3, \ldots, T\}$. For each PET, we denote its full SOC as Q, the charging power as R_c, and the consuming power as R_d when it is running. If it is queuing, no electricity is consumed.

Without loss of any generality, suppose at the current time slot $t = 1$, the SOC level of a PET is smaller than a predefined value, thus a charging task is established and needs to be fulfilled within the remaining operating time L before the battery dies

$$L = \left\lfloor \frac{q(1) - Q_l}{R_d \Delta} \right\rfloor, \; q(1) \in [Q_l, Q] \tag{1}$$

where Δ is the constant time length of each slot, $\lfloor \cdot \rfloor$ is the floor operation, and Q_l denotes an empirical SOC threshold under which PETs must stop service and go to charge. Hence, the PET must charge once in the next L slots to full level, i.e.,

$$\sum_{t=1}^{L} x(t) = 1, \;\; x(t) = \{0, 1\} \tag{2}$$

where $x(t)$ denotes the binary charging decision, and $x(t) = 1$ implies that the PET decides to charge its battery at time slot t. Note that in the online algorithm, at every time slot, a PET driver needs to decide charging at this moment or waiting for future opportunities.

B. Charging Cost and Scheduling Problem

Once a charging decision is made at t, the PET cannot serve customers for a period of time, i.e., the so-called nonservice interval, which can be approximated by $[t, t+\bar{\chi}(t)+\bar{\lambda}(t)+\gamma(t)-1]$. $\bar{\chi}(t)$ is the average traveling time to a CS, which can be readily obtained from varieties of navigation APPs and reflect the traffic condition. $\bar{\lambda}(t)$ denotes the average queuing time. Note that the average is taken over the CSs within a certain geographic region determined by the PET's remaining driving range. Using the average information of CSs is very effective to reduce the complexity of the temporal scheduling problem, whereas more detailed information, i.e., the exact traveling time and queuing time in terms of each CS, will be used in the stage of spatial selection in the next section.

Let $\gamma(t)$ denotes the charging time to a full SOC level. With the assumption that no electricity will be consumed at queuing, it can be expressed as follows:

$$\gamma(t)=\frac{Q-q(t)+R_d\bar{\chi}(t)}{R_c}. \tag{3}$$

In order to reduce the long-term charging cost, which can be nicely approximated by the charging cost per unit SOC (given that the total energy demand is relatively fixed), the critical information used for charging scheduling is the normalized loss of operating income over the amount of electricity to be charged. In such a way, the global objective (i.e., long-term cost) can be decomposed into a series of local tasks (i.e., cost per unit SOC). The charging cost per unit SOC can be expressed as follows:

$$c(t)=\frac{\sum_{\tau=t}^{t+\bar{\chi}(t)+\bar{\lambda}(t)+\gamma(t)-1} g(\tau)}{Q-q(t)+R_d\bar{\chi}(t)},\ t\in[1,L] \tag{4}$$

where the numerator is the total loss and the denominator is the total energy to be charged. $g(\tau)$ denotes the average operating income of PETs at time slot τ. Since in the current stage of temporal scheduling, the exact destination CSs of individual PETs remain unknown, we employ the average traveling time $\bar{\chi}(t)$ and average service income $g(\tau)$ that are independent of PETs' charging decisions to circumvent all uncertainties. Note that both of them are the long-term mean values and can be nicely estimated from historical data by PETs. However, the average queuing time $\bar{\lambda}(t)$ is dependent on the charging decisions of PETs. The current $\bar{\lambda}(1)$ can be observed by the data center, which will broadcast this information to all PETs. The future $\bar{\lambda}(t)$s for $t>1$ are still unknown and considered as random variables to PETs.

Based on $c(t)$, the temporal charging scheduling problem aims to find a time slot that minimizes the charging cost per unit of SOC increment for a charging task, which is formulated as follows:

$$\min_{x}\ \sum_{t=1}^{L} x(t)c(t)$$
$$\text{s.t.}\quad (1), (2). \tag{5}$$

Since several key factors, such as traveling time to CS, queuing status, and remaining SOC level, are comprehensively considered, (5) can nicely reflect PETs' concerns in practice. However, the technical difficulty of solving the above-mentioned problem lies in that only current charging cost, i.e., $c(1)$, can be directly computed, whereas the future charging cost $c(t), t>1$, is not available because $\bar{\lambda}(t), t>1$, is unknown and random. Since $c(t), t>1$, is also random, it makes (5) a stochastic optimization problem that is generally difficult to solve. Thus, an online method is particularly designed in the following.

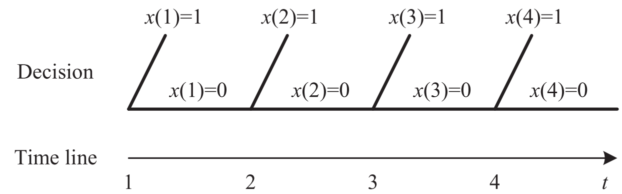

Fig. 2. Demonstration of a decision process.

C. Thresholding Algorithm

As demonstrated in Fig. 2, at each time slot, the driver needs to decide charging at this moment, i.e., $x(t)=1$, or waiting for future opportunities, i.e., $x(t)=0$. For example, if now is $t=1$, the driver only needs to determine the value of $x(1)$, not the future ones $x(2)$, $x(3)$, and $x(4)$. $x(2)$ is determined when now is $t=2$, and so on.

Note that $\bar{\lambda}(t)$ is known for the current slot because it is the current queuing time that can be observed by CSs and announced to PETs, but the future $\bar{\lambda}(t)$s are unknown. Meanwhile, the current charging cost $c(t)$ is also known. Thus, the intuition of the decision is: if current cost $c(t)$ is smaller than the expected future cost, denoted by $f(t)$, that can be calculated according to the probability density function (PDF) of future $\bar{\lambda}(t)$,[1] the PET will charge now; otherwise, it will wait for future opportunities. This idea is learned from [32], and gives us the following simple and efficient thresholding method:

$$x(t)=\begin{cases}1, & c(t)\le f(t)\\ 0, & c(t)>f(t).\end{cases} \tag{6}$$

Intuitively, the PET will charge now if current charging cost is smaller than $f(t)$. Otherwise, at the next slot $t+1$, the PET will compare again the charging cost at that moment with the future expectation. In other words, $f(t)$, $t\in[1,L]$, can be seen as a series of thresholds for online decision making.

Thus, the task becomes the computation of $f(t)$, which in fact can be obtained in advance/offline according to the time-domain statistics of $\bar{\lambda}(t)$ in a backward fashion as detailed below.

Slot L: The PET is about to run out of battery and has to start charging at this slot. Therefore, $f(L)$ can be directly set to a sufficiently large value M, i.e.,

$$f(L)=M \tag{7}$$

such that $c(L)\le f(L)$ always holds.

[1] We assume that future $\bar{\lambda}(t)$ follows a probabilistic distribution approximated from historical data points.

Slot $L-1$: The threshold at slot $L-1$ is the expected future charging cost, i.e., the expected charging cost at slot L, as follows:

$$f(L-1) = E\left[c(L)\right] \tag{8}$$

where E is the expectation with respect to the random variable $\bar{\lambda}(L)$. Since the charge at slot L is a full effort, the electricity needed is $Q - Q_l$ and the charging time is $\gamma(L) = \frac{Q-Q_l}{R_c}$. Consequently, $E\left[c(L)\right]$ is

$$E\left[c(L)\right] = E\left[\frac{1}{Q-Q_l}\sum_{\tau=L}^{L+\bar{\chi}(L)+\bar{\lambda}(L)+\gamma(L)-1} g(\tau)\right]. \tag{9}$$

Furthermore, it can be transformed into the following computable form:

$$\begin{aligned} E\left[c(L)\right] &= \frac{1}{Q-Q_l}\left(\sum_{\tau=1}^{\bar{\chi}(L)+\gamma(L)} g(\tau+L-1)\right. \\ &\quad \left. + E\left[\sum_{\tau=1}^{\bar{\lambda}(L)} g(\tau+L+\bar{\chi}(L)+\gamma(L)-1)\right]\right) \\ &= \frac{1}{Q-Q_l}\left(\sum_{\tau=1}^{\bar{\chi}+\gamma(L)} g(\tau+L-1)\right. \\ &\quad \left. + \sum_{\tau=1}^{\infty} g(\tau+L+\bar{\chi}(L)+\gamma(L)-1)P\left[\bar{\lambda}(L)\geq\tau\right]\right) \end{aligned} \tag{10}$$

where $P\left[\bar{\lambda}(L)\geq\tau\right]$ is the probability of $\bar{\lambda}(L)\geq\tau$ for any given τ, and can be obtained from the PDF of $\bar{\lambda}(L)$.

Slot t, $t \in 1,2,3,\ldots,L-2$: The PET would be more cost efficient to charge at slot t than in the future if $c(t) \leq f(t)$; otherwise, it should wait for future opportunities. Thus, the expected cost of charging at slot t or thereafter can be obtained by the law of total probability as follows:

$$f(t) = \alpha(t+1)\tilde{c}(t+1) + (1-\alpha(t+1))f(t+1) \tag{11}$$

where $\alpha(t+1)$ is the probability of charging at $t+1$, and $\tilde{c}(t+1)$ is the corresponding conditionally expected cost at $t+1$. Note that for a certain t, $\alpha(t+1)$ and $\tilde{c}(t+1)$ are functions of $\bar{\lambda}(t+1)$, and $\bar{\lambda}(t+1)$ is a random variable. That is

$$\alpha(t+1) = P\left[c(t+1) \leq f(t+1)\right] \tag{12}$$

and

$$\begin{aligned} \tilde{c}(t+1) &= E\left[c(t+1) | c(t+1) \leq f(t+1)\right] \\ &= \frac{E\left[c(t+1)\mathbf{1}(c(t+1) \leq f(t+1))\right]}{\alpha(t+1)} \end{aligned} \tag{13}$$

where $\mathbf{1}(c(t+1) \leq f(t+1)) = 1$ when $c(t+1) > f(t+1)$, and 0 otherwise.

The backward induction method used to compute thresholds $f(\tau)$ is summarized as Algorithm 1.

Note that the thresholding algorithm mainly involves computing thresholds for remaining operating time offline and comparing thresholds with real-time costs online. On the one hand, the thresholds are computed via backward induction and each per-step computation consists of only basic addition and multiplication. On the other hand, the real-time comparison is trivial. Jointly, the complexity of the thresholding method scales linearly with the remaining operating time L of an EV, which is upper bounded in practice due to battery capacity.

Algorithm 1: Calculation of the Threshold.

Input: $t, q(t), Q_l, Q, R_d$, and historical data of queuing time $\lambda(t)$ and operating income $g(t)$

Output: f

Initialization:
Compute L according to (1);
Let M be a constant large enough and set $f(L) = M$;
$t \leftarrow L-1$;
Compute $f(t)$ according to (8);
while $t > 1$ **do**
  $t \leftarrow t-1$;
  Compute $\alpha(t+1), \tilde{c}(t+1)$ based on the known probability density of queuing time $\bar{\lambda}(t+1)$ and operating income $g(t+1)$ using (12), (13);
  Compute the expected charging cost $f(t)$ using (11);
end while
$f \leftarrow (f(1),\ldots,f(L-1),f(L))$;

III. Spatial Selection Problem

After a PET decides to charge at a slot, the driver still needs to choose a CS from the surrounding ones, which associate with different traveling time and queuing time. It is notable that many PETs in the same region request to charge at the same time slot, and a PET's individual selection of CS may affect the queuing time of other PETs that arrive later at the same CS. Thus, the spatial selection problem turns into an interaction among multiple PETs. To tackle this technical challenge, a game-theoretic approach is proposed to solve the spatial selection problem in a distributed way. That is, every driver will make his own selection and NE can be achieved through iterations. An advantage of applying the game approach is that the fairness of the selection can be guaranteed, because no PET can benefit by unilaterally deviating from NE. Since the temporal scheduling decision has already been made in the previous section, in this section, we drop the notation of time slot for simplicity.

A. Duration of Nonservice Interval

Let $\mathbb{I}$ denote the set of PETs that request charging, and $\mathbb{J}$ denote a set of candidate CSs. As the game approach will be used, also let s_i denote the strategy of the ith PET, and $s_i = j$ implies that the ith PET selects the jth CS as its target station ($\forall i \in \mathbb{I}, \forall j \in \mathbb{J}$). Let the set $\vec{s} = \{s_i | i \in \mathbb{I}\}$ denote the strategy profile of the PET set $\mathbb{I}$.

Similar to the previous temporal scheduling, the normalized charging cost (4) will also be seen as the objective to be minimized in spatial selection. However, (4) can be reasonably simplified. First, the average income $g(i)$ in (4) can be neglected since a temporal decision has already been made. Second, no matter which CS is selected, the electricity to be charged is roughly the same because CSs are usually dense enough. Therefore, the denominator in (4) can also be ignored. Consequently, the cost becomes the duration of nonservice interval, which is the objective to be minimized and can be written as follows:

$$p_i^j = \chi_i^j + \gamma_i^j + \lambda_i^j - 1 \tag{14}$$

where χ_i^j, γ_i^j, and λ_i^j denote, respectively, the traveling time of PET i to CS j, the corresponding charging time, and queuing time (approximated by the queuing length). χ_{ij} depends on distance and traffic conditions, but can be easily obtained from many real-time navigation applications. Therefore, χ_i^j and γ_i^j are seen as known parameters. Meanwhile, they are also irrelevant to other PETs' selections. Therefore, they can be rewritten as $\chi_i^{s_i}$ and $\gamma_i^{s_i}$ with $s_i = j$ to highlight the fact that they only depend on the choice of PET i.

On the other hand, λ_i^j can be influenced by others because early arrivers will increase the queueing time of later arrivers. To highlight this point, λ_i^j is replaced by $\lambda_i^{\vec{s}}$, and the duration of nonservice interval is rewritten as follows:

$$p_i^{\vec{s}} = \chi_i^{s_i} + \gamma_i^{s_i} + \lambda_i^{\vec{s}} - 1. \tag{15}$$

Suppose each PET is self-interested and only aims to reduce its own cost function, it would change their strategies unilaterally if there is a better one. Thus, a game approach is proposed to ensure the fairness and efficacy of the selection of CSs, as detailed in the following.

B. Game-Based Impartial Solution

We describe the decision-making process of the spatial selection as a game, and the impartial decision as an NE strategy profile of the game [33], [34]. The game is defined as follows.

1) *Player set* $\mathbb{I}$*:* the PET set that requires charging.
2) *Strategy space* $\vec{s} \in \mathbb{S}$*:* all feasible strategy profiles $\vec{s}$ of set $\mathbb{I}$. Often, we use s_{-i} to denote the strategies of all the other PETs in the set $\mathbb{I}$ except PET i, so that $\vec{s}$ can be replaced by (s_i, s_{-i}) sometimes. Also define $(s'_i, s_{-i}) \in \mathbb{S}$ as an alternative strategy profile, where $s'_i \in \mathbb{J}$ denotes any other feasible strategy of PET i except s_i.
3) *Cost function set* $\{p_i^{\vec{s}}\}$*:* the summation of the traveling time and queuing time for each PET i, as defined in (15).

Then, we have the following theorem.

Theorem 1: An NE exists for the above-mentioned game, from which it is unprofitable to deviate unilaterally for any single player. That is, there exists a strategy profile $\vec{s} \in \mathbb{S}$ such that

$$p_i^{(s_i, s_{-i})} \le p_i^{(s'_i, s_{-i})} \quad \forall i \in \mathbb{I}. \tag{16}$$

The convergence to an NE can be achieved by Algorithm 2.

Proof: We describe the proof in three steps, which are also the essences of Algorithm 2. We first prove that an NE exists in any single player set, then show that a new NE can be found when a new player is added. At last, it is concluded by induction method that an NE always exists in this game for any player set.

Algorithm 2: Search of NE Strategy.

Input: $\chi_{ij}, \gamma_{ij}, \forall i \in \mathbb{I}(t), \forall j \in \mathbb{J}$
Output: $\vec{s}$
Initialization: $\mathbb{U} = \emptyset, \vec{s} = \emptyset$;
repeat
  Randomly pick a player $l, \forall l \in \mathbb{I} \setminus \mathbb{U}$;
  $\vec{s} \leftarrow$ ITERATOR $(\mathbb{U}, l, \vec{s})$;
  $\mathbb{U} \leftarrow \mathbb{U} \cup \{l\}$;
until $\mathbb{U} = \mathbb{I}$

function ITERATOR $(\mathbb{U}, l, \vec{s})$
  $s_l \leftarrow$ compute strategy of player l that minimizes (15) based on $\vec{s}$;
  if $(\vec{s}, s_l)$ is an NE strategy of player set $\mathbb{U} \cup \{l\}$ **then**
    return $(\vec{s}, s_l)$;
  else
    A player $k \in \mathbb{U}$ will change unilaterally to a strategy that minimizes (15);
    return ITERATOR $(\mathbb{U} \cup \{l\} \setminus \{k\}, k, (s_{-k}, s_l))$;
  end if
end function

Before approaching these steps, define $\mathbb{U} \subseteq \mathbb{I}$ as a stable subset of $\mathbb{I}$, which contains an NE strategy profile $\vec{s}_{\mathbb{U}}$.

Step 1. Any single player subset has an NE strategy, which is also a stable subset: For any single PET subset $\{i\}$, a strategy s_i that satisfies $p_i^{s_i} \le p_i^{s'_i}$ is its NE strategy. In other words, by enumerating all possible CSs, a PET can easily identify the one with the lowest cost.

Step 2. For any stable subset, when a new player is randomly added, the new subset can always find a new NE strategy and thus remain stable: Randomly pick a PET $l \in \mathbb{I} \setminus \mathbb{U}$, and add it into subset $\mathbb{U}$. PET l would select CS s_l satisfying $p_l^{\vec{s}_{\mathbb{U}} \cup s_l} \le p_l^{\vec{s}_{\mathbb{U}} \cup s'_l}$ as its strategy, where $\vec{s}_{\mathbb{U}} \cup s_l$ is a strategy profile of PET set $\mathbb{U} \cup \{l\}$.

Apparently, PETs that also select s_l but arrive after the newly added PET l will be influenced because their queue length will increase by 1 due to the insertion of PET l. Let $k \in \mathbb{B} := \{k | s_k = s_l, \chi_{k s_k} \ge \chi_{l s_l}, \forall k \in \mathbb{U}\}$ denote the PETs influenced by the newly added PET l. Thus, the queue length for PET k after the insert of PET l becomes

$$N_k^{\vec{s}_{\mathbb{U}} \cup s_l} = N_k^{\vec{s}_{\mathbb{U}}} + 1 \tag{17}$$

where the cost of PET k will increase consequently, i.e.,

$$p_k^{\vec{s}_{\mathbb{U}} \cup s_l} \ge p_k^{\vec{s}_{\mathbb{U}}}. \tag{18}$$

With the new cost $p_k^{\vec{s}_{\mathbb{U}} \cup s_l}$, PET k may or may not change its strategy. All possibilities of its decision fall into the following two categories.

1) The subset $\mathbb{U}$ remains stable with the strategy profile $\vec{s}_{\mathbb{U}}$ with the following conditions:
   a) when $\mathbb{B} = \emptyset$. That is, there is no PET influenced by the newly added PET l; and
   b) when $\mathbb{B} \ne \emptyset$ but no PET in the set $\mathbb{B}$ has an incentive to change its strategy. In other words, although the

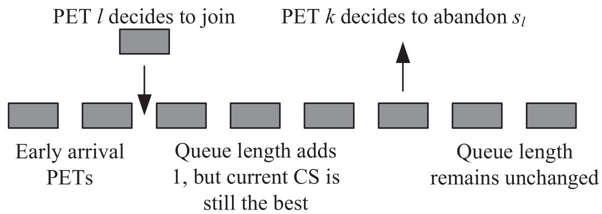

Fig. 3. Demonstration of the change of queue length at a CS.

cost of PET k increases, but current strategy is still better than other alternative ones. That is

$$p_k^{(s_k, s_{-k}) \cup s_l} \leq p_k^{(s_k, s_{-k}) \cup s_l} \quad \forall k \in \mathbb{B}. \tag{19}$$

Thus, the new strategy profile $\vec{s}_{\mathbb{U}} \cup s_l$ is an NE strategy profile of the subset $\mathbb{U} \cup \{l\}$.

2) The subset $\mathbb{U}$ becomes unstable. That is, when $\mathbb{B} \neq \emptyset$ and there exists at least one PET in $\mathbb{B}$ that has an incentive to change its strategy.

Sort the PETs in the set $\mathbb{B}$ by arrival time in chronological order, and identify the first PET k that has an incentive to change its strategy. When PET k abandons the strategy s_l, all other PETs in the set $\mathbb{B}$ that arrive at CS s_l after PET k would have no incentive to change their strategies now because the queue length for them would remain unchanged by inserting PET l and then removing PET k. Consequently, their costs also remain unchanged.

A simple example can demonstrate this process, as shown in Fig. 3. Let the gray boxes be the PETs that intend to charge at the same CS. Assume that the left two PETs are early arrivals, and thus will not be influenced by the decision of PET l. When PET l decides to join this CS, let the middle three PETs be the ones whose queue length will increase by 1, but the optimal decision is still the same CS. Therefore, they will not change their decisions. Then, let PET k have a better choice after PET l inserts, thus it will change its decision and leave this queue. Consequently, the queue length for the left two PETs will remain the same and they do not need to change their choices.

Thus, by inserting PET l and then removing PET k, the original stable set $\mathbb{U}$ becomes a new stable set $\mathbb{U} \cup \{l\} \setminus \{k\}$, and the associated NE strategy profile is $s_{-k} \cup s_l$. In fact, this process means that PET k is replaced by a new PET l that has a higher priority in CS s_l.

Then, PET k needs to find another CS other than s_l. This process is the same as adding PET l into the queue at a certain CS, as described previously. The insertion of PET k at a certain CS may result in the change of strategy of another PET at the same CS. Thus, this is a repetitive process.

Next, we proceed to show that this process will cease in finite steps without cycling. Consider the above-mentioned PET k that changes its strategy due to the insertion of PET l, there are following two possibilities.

1) PET k switches among CSs and never repeats. Without the insertion of other PETs before it in the queue, PET k has made the optimal decision. Therefore, if it switches to another CS, its cost is no lower than in the original position.

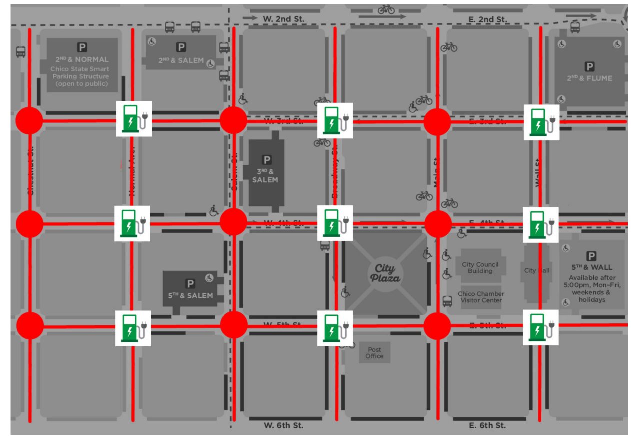

Fig. 4. Meshed road network.

2) PET k switches back to the original CS at some point. Note that when a PET decides to change its choice due to the insertion of another PET, the total queue length at that CS remains the same. Every time PET k switches back, the queue length of PETs before it will be nondecreasing. Therefore, it will have a no lower cost.

To summarize, when PET k decides to change a CS, it will never have a lower cost than that in its original position. Due to the limited choices of CSs and that the cost is finite by default, PET k will settle down at one CS. Note that here PET k is general, therefore eventually all PETs in the subset $\mathbb{U} \cup \{l\}$ will find suitable CSs and no one will unilaterally change its strategy. That is, $\mathbb{U} \cup \{l\}$ is a stable subset.

Step 3: According to the induction method, there is an NE for any player set $\mathbb{I}$. ■

The procedures described in the proof are summarized in Algorithm 2 to find an NE strategy profile in finite steps.

Note that the above-mentioned game of spatial selection reduces to a repeated finite potential game, and the worst case complexity of Algorithm 2 is IJ^{I-1} while its average complexity over random game instances is only $e^{\gamma} I + O(I)$, where γ is the Euler constant [35]. In practice, the game-based solution is not likely to bring heavy computation and communication burden for two reasons. First, normally the charging requests of a PET fleet spread over different time slots and regions, which means only a small portion will charge at the same time in the same region. Second, the information center can perform the game for PETs since the information center knows the PETs' positions and thus the traveling time to CSs, as well as the queuing status at CSs. Therefore, the information center can send the coordination result to PETs, and no communication is needed among PETs.

IV. Numerical Results

In this section, we verify the performance of proposed algorithms through simulations on MATLAB R2015b. In the simulation, we consider a meshed road network of a city region, as shown in Fig. 4. The PET runs randomly on the road network if there is no passenger. Passengers and their destinations are

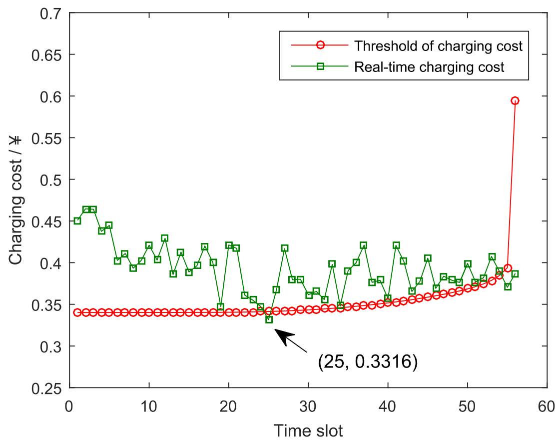

Fig. 5. Temporal scheduling case.

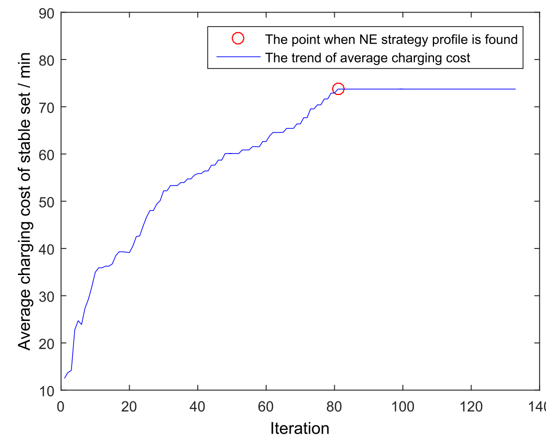

Fig. 6. Trend of average charging cost of a stable set.

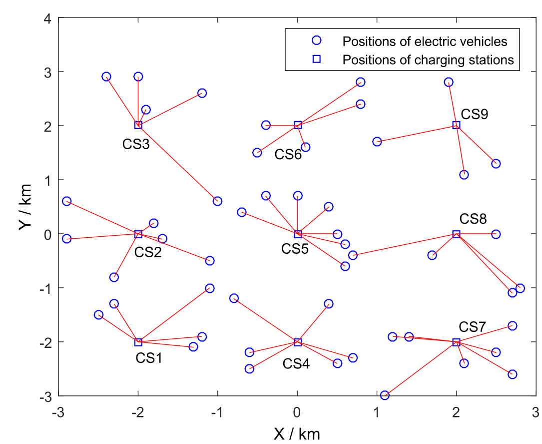

Fig. 7. Recommendation result of spatial selection.

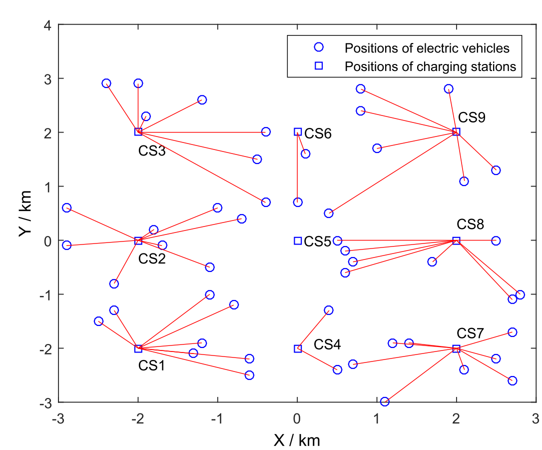

Fig. 8. Recommendation result of spatial dispatch after setting e_j.

generated randomly using the uniform distribution on the road network. Once a PET meets a passenger, it will send the passenger to destination and earn payment proportional to the distance. The CSs are uniformly distributed on the road network. Note that, for simplicity, we ignore the impact of traffic lights. Then, consider a PET with the battery capacity $Q = 60$ kW · h, battery lower bound $Q_l = 6$ kW · h, consuming power rate $R_d = 6$ kW, charging rate $R_c = 30$ kW, and one time slot is set as 2.5 min. The average driving speed of the PET is set to 24 km/h or 1 km/slot. Note that the normal distribution with proper mean and variance is employed to generate the average queuing time $\bar{\lambda}(t)$ for simplicity.

A. Performance of Temporal Scheduling

In Fig. 5, a schedule is given to demonstrate the decision-making process using Algorithm 1. Suppose that the PET sends a charging request at time slot 1, and it would not charge until time slot $t = 25$ when the real-time charging cost becomes lower than the threshold. As shown in Fig. 5, it is interesting to find that the charging cost happens to be the minimum. Though this is not always guaranteed, it shows that our algorithm tries to capture the expected minimum cost in an online fashion.

B. Performance of Spatial Selection

In order to investigate the performance of spatial selection, we consider a 6 km × 6 km area, in which nine CSs each equipped with six charging piles are uniformly deployed. Assume there are 50 PETs with random positions requesting battery charging. Set the value of λ_{0j} of the CSs as 0 for simplicity. As shown in Fig. 6, the proposed algorithm finds the NE strategy quickly in 81 iterations, which take only seconds on a laptop.

In Fig. 7, the selection result is illustrated. The numbers of PETs assigned to different CSs are basically balanced because Algorithm 2 considers not only the distance but also the queuing length of different CSs. A nearby CS with long queuing length may not be favored by PETs. If we set the initial number of PETs at the middle column CSs as 6,10,6, the selection algorithm avoids assigning PETs to these CSs, as shown in Fig. 8.

C. Performance of Joint Coordination

Now, we consider a longer time horizon in another 10 km × 10 km area, where 25 CSs each equipped with 8 charging piles are uniformly deployed, and 1000 PETs are running in this area with random initial locations. Note that the ratio of the PET number to the charging pile number is 5 : 1, which is sufficient to complete the charging task. Thus, the traveling

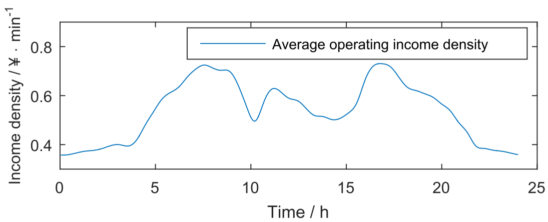

Fig. 9. Average operating income density at different slots.

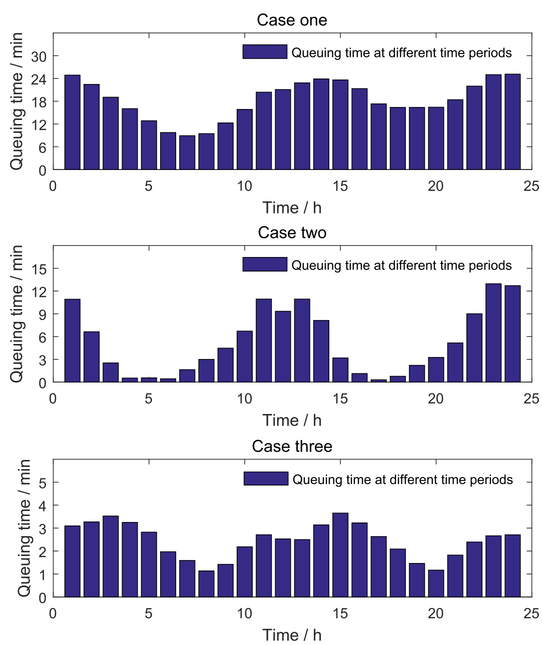

Fig. 10. Queuing time in temporal domain of different cases.

time, charging time, and queuing time can be generated from CSs in the simulation process automatically.

First, we simulate the PET operating process for 20 days without any coordination to collect historical data of queuing time, based on the given operating income information, as shown in Fig. 9. Then, we simulate the PET operating process for ten days under three different cases detailed as follows. The numerical results are shown in Figs. 10–12 and Table I.

1) *Case one. No coordination:* In this case, PETs only consider the SOC when selecting charging slots, that is, a PET will charge when its SOC is lower than a threshold. Then, a PET will select the closest CS.
2) *Case two. Temporal scheduling:* PETs select the charging time according to Algorithm 1, and then select the closest CSs.
3) *Case three. Temporal–spatial coordination:* PETs select charging slots by Algorithm 1, and CSs by Algorithm 2.

As shown in Fig. 10, all the three cases maintain the similar load profile that reflects the daily demand pattern. However, in case 1, the average queuing time per charge over all CSs at different hours is much longer than that in the other two. With increasing level of scheduling and coordination, the average queuing time decreases tremendously in cases 2 and 3. More

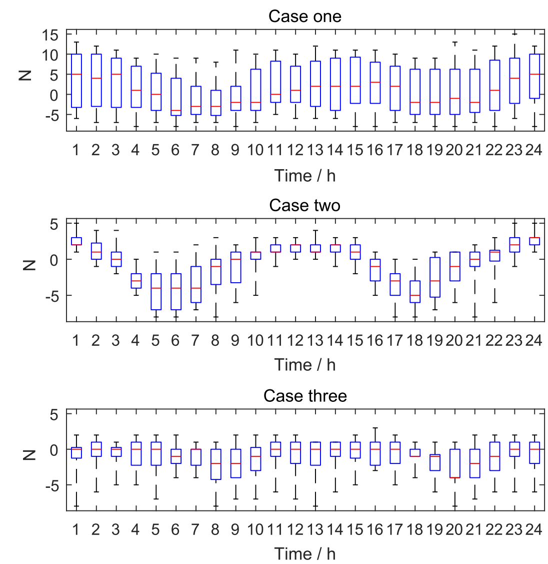

Fig. 11. N in temporal domain of different cases.

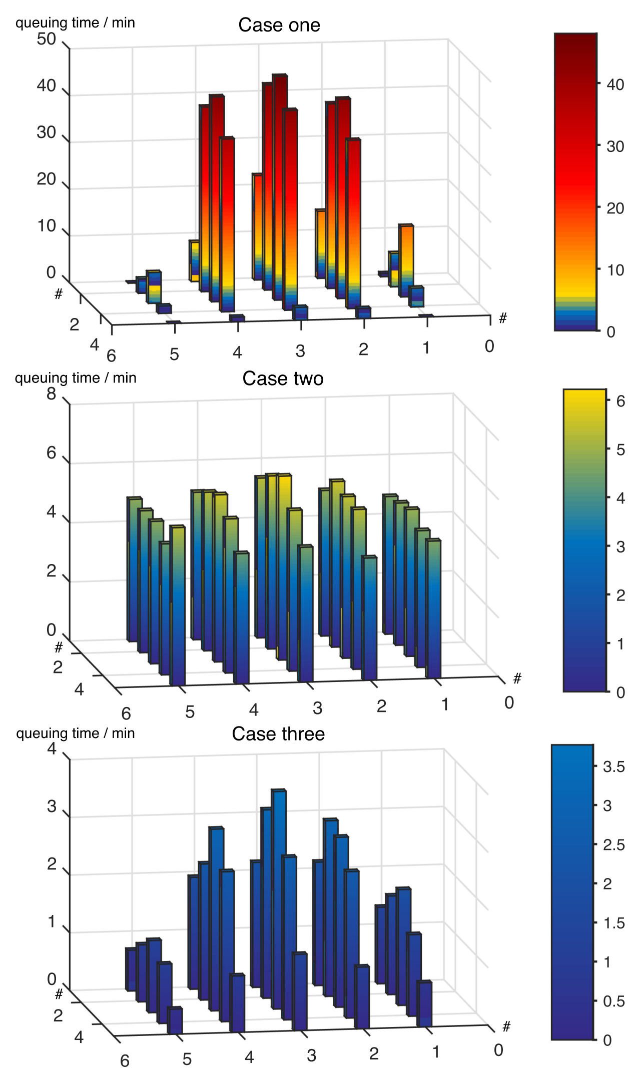

Fig. 12. Queuing time in spatial domain of different cases.

TABLE I
COORDINATION RESULTS OF DIFFERENT CASES

Item \ Case	One	Two	Three
Average income of PETs (¥/day)	592.41	627.70	635.81
Average travelling time of PETs (min)	6.00	9.88	7.37
Average queuing time of PETs (min)	60.67	13.49	5.27
Average queuing rate of PETs (%)	67.38	53.22	35.37
Average idle rate of charging piles (%)	23.52	18.17	16.96

specifically, let N denote the queuing length when $N \geq 0$, and the number of idle charging piles when $N < 0$. Fig. 11 shows the statistics of N over a day in the three cases, which indicates the inefficient use of charging piles without scheduling and the huge potential for improvement with our two-stage scheme. On the other hand, Fig. 12 also suggests in case 1 the average queuing time per charge over ten days at different CSs is way longer than in the other two. Besides, the charging piles are unevenly utilized across different CSs with part of them heavily congested, which, however, is significantly alleviated through temporal and spatial coordination.

Meanwhile, we also investigate the PET income, queuing rate (ratio between queuing time and charging time), and the charging pile idle rate (ratio between idle piles and total piles). As shown in Table I, Algorithm 1 can significantly reduce the queuing rate of PETs and the idle rate of charging piles, and augment the operating income of PETs, although the traveling time of PETs may increase a little bit. Moreover, Algorithm 2 can take a step further and obtain even better results. Therefore, the proposed methods are capable of improving the utilization efficiency of charging infrastructure, and also helping PETs avoid long queuing time, thus acquiring more operating income.

V. CONCLUSION

In this paper, we propose a new solution to the charging coordination problem of a PET fleet, which aims to lower the charging cost mainly by reducing queuing time. Since the exact future positions and queuing time remain unknown for PETs, we divide the coordination problem into two stages. In the first stage, we propose a temporal scheduling algorithm based on a thresholding method, which helps the PET to choose a good time slot for charging. In the second stage, we proposed a spatial selection algorithm based on a game-theoretical approach to advise PETs to proper CSs, which also ensures fairness among PETs. It is worth noting that both algorithms are fully distributed, thus can nicely fit into practice as each PET makes its own decision. The simulation results demonstrate that the proposed algorithms exhibit good performances in reducing the charging cost for PETs, enhancing the utilization ratio for CSs, and flattening the unevenness of charging request for power grids.

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