# Intelligent Parking Garage EV Charging Scheduling Considering Battery Charging Characteristic

Zhe Wei, *Student Member, IEEE*, Yue Li, Yongmin Zhang, *Member, IEEE*, and Lin Cai, *Senior Member, IEEE*

***Abstract*—This paper studies the electric vehicle (EV) charging scheduling problem under a parking garage scenario, aiming to promote the total utility for the charging operator subject to the time-of-use (TOU) pricing. Different from most existing works, we develop a multicharging system incorporating the practical battery charging characteristic, and design an intelligent charging management mechanism to maximize the interests of both the customers and the charging operator. First, to ensure the quality of service for each client, we implement an admission control mechanism to guarantee all admitted EVs' charging requirements being satisfied before their departure. Second, we formulate the charging scheduling process as a deadline constrained causal scheduling problem. Then, we propose an adaptive utility oriented scheduling (AUS) algorithm to optimize the total utility for the charging operator, which can robustly achieve low task declining probability and high profit. The charging operator can also apply the discussed reservation mechanism to mitigate the performance degradation caused by the charging information mismatching with vehicle stochastic arrivals. Finally, we conduct extensive simulations based on realistic EV charging parameters and TOU pricing. Simulation results exhibit the effectiveness of the proposed AUS algorithm in achieving desirable performance compared with other benchmark scheduling schemes.**

***Index Terms*—Battery charging characteristic, electric vehicle (EV) charging, hierarchical control, scheduling.**

## I. Introduction

WITH the advantage of energy saving and environmental friendliness, electric vehicles are increasingly favored by the market. In Norway, the electric vehicle (EV) sales have already reached 22% of the new car sales in the first quarter of 2015 [1]. However, one of the major roadblocks to promote the EV penetration is the lack of convenient public charging infrastructure [2]. Home charging is unavailable for many EV users in the metropolitan area. More and more EV customers need to find a convenient public place for charging. It is anticipated that the future garages, such as the parking lots for office buildings or business districts, can also provide EV charging services and function as EV charging stations [3], [4]. However, given the likely future high EV penetration rate, without a proper coordination of the charging activities, either the charging operator has to decline some charging service requests resulting in revenue loss unnecessarily or the customers may lose the potential charging opportunity unwillingly [5], [6]. To mitigate these adverse effects, it is crucial and necessary to design an intelligent charging system and apply efficient scheduling algorithms to guarantee both the charging operator and the charging customers' interests. In addition, with the yearly increasing electricity load, the utility companies need to regulate the market by different pricing schemes to maintain the stability of the grid. As time-of-use (TOU) pricing has been widely adopted in current electricity markets [7]–[9], we also need to consider the impact of electricity price on the EV charging scheduling activities to keep a profitable operation for the charging operator.

The charging efficiency significantly affects the charging duration in the actual charging process. However, for most of the existing works on EV charging scheduling, the charging efficiency variation caused by the battery state of charge (SOC) change has not been thoroughly investigated [7]. Due to the electrochemical characteristic of EV batteries, the charging power decreases substantially for the higher SOCs with the increase of the internal resistance, which causes the charging efficiency significantly reduced along with the charging process [10]. There are two factors affecting the operation of an EV charging station. One is the profit, the most fundamental motive; the other is the service reputation, related to whether the customers' charging requirements can be satisfied before their specified departure time. Typically, the customers pay bills based on the power consumptions. However, providing charging services at the high tariff period is less profitable for the charging operator. Charging the EVs with high SOC is very inefficient, they may occupy the charging facilities for a longer time owing to the low charging efficiency and lead to potential profit reduction. These battery inherent characteristics make the EV charging

Manuscript received April 21, 2017; revised June 29, 2017; accepted July 17, 2017. Date of publication August 17, 2017; date of current version December 15, 2017. This work was supported in part by the Natural Sciences and Engineering Research Council of Canada. *(Corresponding author: Lin Cai.)*

The authors are with the Department of Electrical and Computer Engineering, University of Victoria, Victoria, BC V8W 3P6, Canada (e-mail: weizhe@uvic.ca; liyue331@uvic.ca; ymzhang@uvic.ca; cai@ece.uvic.ca).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIE.2017.2740834

scheduling a challenging inflexible problem. Thus, to keep a profitable operation, it is crucial for the charging operator to well schedule the different charging requirements taking the effects of the charging power and electricity price changes into consideration, which is the primary motivation of this work.

The main contributions of this work are fourfold. First, we design an intelligent multicharging system suitable for the garage charging operator to efficiently provide charging service and manage the charging process taking into account the interests of both customers and business. Second, we model the battery charging characteristic change during the actual charging process combined with its intrinsic electrochemical characteristic and analyze its impact on the EV charging scheduling process. Third, we design an efficient scheduling algorithm to maximize the total utility for the charging operator under the premise of customer satisfaction assurance. Fourth, we consider the practical stochastic mobility scenarios and discuss a reservation mechanism for the charging operator to adjust the expected profit and task declining cost, and thus to mitigate the performance degradation caused by the charging information mismatching. Extensive simulations under practical charging settings are conducted to demonstrate the excellent performance of the proposed algorithm compared with other benchmark solutions.

The rest of the paper is organized as follows. Section II presents the related work. System model and design objective are introduced in Section III. The battery charging characteristic is analyzed in Section IV. In Section V, the admission control and scheduling algorithms are proposed and analyzed. Case studies are presented in Section VI, followed by the concluding remarks in Section VII.

## II. Related Work

EV charging problems have been studied mainly from three different perspectives, smart grid oriented, aggregator oriented, and customer oriented [11]. In this paper, we concentrate on the aggregator oriented perspective. For this category, there have been extensive research works conducted on the profitable operations for the charging operator [7], [12]–[18]. In [13], a real-time power allocation strategy was proposed to improve the self-consumption of PV energy and reduce the charging cost for a commercial building microgrids containing EVs and PV system. Including the mismatching risk between the predicted and actual charging loads, a risk-aware day ahead scheduling was proposed in [16] to minimize the cost for the charging operator. However, the power allocation results are greatly affected by the prediction accuracy. An online coordinated charging decision algorithm was proposed in [17] to minimize the energy cost without knowing the future charging information. The designed algorithm achieved the best known competitive ratio, but the service capacity of the charging station was not taken into consideration. In [7], [18], and [19], the scheduling for EV charging with TOU pricing was investigated. The load management technique was developed to shift the deferrable load to the low price time to minimize the peak load and reduce the charging cost. However, the EV's charging duration and demand constraints were not investigated in these works.

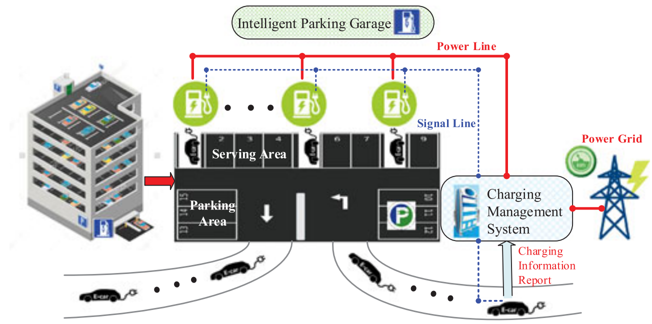



Fig. 1. Intelligent parking garage EV charging system.

Other groups of work utilized the control, scheduling, and optimization methods to improve the quality of service during the charging process [20]–[27]. In [22], optimal power allocation and EV arrival rate adjustment strategies were investigated to reduce the blocking probability of the EV charging requirements. An admission control algorithm was developed in [24] and [25] to achieve the maximum profit. However, the charging requirement of each customer cannot be guaranteed under the designed schemes. In [26], the minimization of EV charging waiting time via scheduling charging activities spatially and temporally in a large-scale road network was investigated. A dc fast charging model was incorporated into the queuing analysis as well as the revenue model in [27]. By limiting the threshold on requested SOC in an overload condition, the revenue was increased, and the blocking probability of the arriving EVs was decreased. But how to choose the best requested SOC and its corresponding effect on the performance was not fully investigated. Consequently, how to achieve a profitable charging operation under the premise of customer charging QoS assurance has not been well addressed in most existing works, which motivates the study in this paper.

## III. System Model and Design Objective

Fig. 1 shows the scheme of an intelligent multicharging system in a parking garage. When an EV arrives at the parking garage, it reports its charging information, i.e., the arrival time, preferred departure time, current, and requested battery SOCs, to the garage's charging management system (CMS). The CMS decides whether to admit or to decline the customers' charging requirements and manages the power supply to activate or deactivate the in-facility EVs' charging activities based on the utilized electricity pricing scheme and its scheduling mechanism. The whole charging procedure is controlled by an intelligent charging network. Each admitted vehicle is parked in the charging area and is connected to the charging network. The power dispatching is controlled by the CMS. All the charging activities are automatically switched. Those charging service declined EVs are parked in the noncharging area. For easy reference, the important notations are listed in Table 1.

### *A. System Model*

According to the traffic data collected from the Canton of Zürich [28], we model the EV mobility/parking activity in

TABLE I
NOTATIONS

| Symbol | Description |
|---|---|
| $M$ | Charger number. |
| $T$ | Total time slot number. |
| $t$ | Current time slot. |
| $i$ | Task index. |
| $\lambda_k$ | Average arrival rate for the $k$th period. |
| $t_i^a$ | $i$th EV arrival time. |
| $t_i^d$ | $i$th EV departure time. |
| $S_i^{\text{ini}}$ | $i$th EV initial battery SOC. |
| $S_i^{\text{req}}$ | $i$th EV requested battery SOC. |
| $\mathbf{I}$ | Active task index set. |
| $\mathbf{L}$ | Active task charging requirement set. |
| $\mathbf{E}$ | Active task charging energy set. |
| $t_h^b$ | High price period beginning time. |
| $t_h^e$ | High price period ending time. |
| $t_l^b$ | Low price period beginning time. |
| $t_l^e$ | Low price period ending time. |
| $P_0$ | Battery maximum charging power. |
| $B$ | Rated battery capacity. |
| $\mathbf{A}$ | Charging allocation result matrix. |

a workplace parking garage as follows. Suppose the parking garage charging service hours per day is equally divided into $T$ time slots with each slot duration as $\Delta t$. Each arrived EV is sequentially indexed. Denote the arrival time and customer anticipated departure time of the $i$th arrived EV as $t_i^a$ and $t_i^d$, where $t_i^a < t_i^d \leq T$. The arrivals of EVs follow a Poisson process [26], [29], [30]. According to the vehicular mobility/parking pattern in real life, the arrival rates of the incoming EVs at different periods of the day are different. Thus, the $T$ time slots a day are divided into $K$ periods with each period duration as $D_k$. For each period, it has different arrival rates denoted as $\lambda_k, k = 1, 2, \ldots, K$. Considering the feature of a workplace parking garage, the departure time of the EVs are assumed to follow a truncated Gaussian distribution [31] $\mathcal{N}(t_d, \sigma_d^2)$, where $t_d$ is the mean of the leaving time and $\sigma_d$ is the standard deviation.

The charging requirement of an EV is determined by both of its initial battery SOC, $S_i^{\text{ini}}$, when it arrives at the parking garage, where $0 \leq S^{\text{ini}} < 1$, and the requested SOC, $S_i^{\text{req}}$, the objective SOC the customer wants the battery to reach at the departure, where $S^{\text{ini}} < S^{\text{req}} \leq 1$. Most users typically charge their EVs at the levels that were associated with the battery warnings [32]. Consequently, the initial EV battery SOC of a recharge cycle is assumed to follow a truncated Gaussian distribution [31] $\mathcal{N}(\mu_S, \sigma_S^2)$, where $\mu_S$ is the battery warning SOC, and $\sigma_S$ is the standard deviation. The requested SOC of each EV depends on many issues like the customer's preferred departure time, the charging rate, and the electricity price, etc. Each EV's charging requirement can be regarded as a *Task*, defined as

$$\mathcal{T}_i = (t_i^a,\, t_i^d,\, S_i^{\text{ini}},\, S_i^{\text{req}}). \tag{1}$$

The charging operator purchases electricity from the utility company subject to a time-varying wholesale price. The wholesale price at different time slots a day is defined as a vector $\mathbf{Pr}_w = [Pr_w^1,\, Pr_w^2,\, \ldots,\, Pr_w^T]$. Currently, most utility companies adopt the TOU pricing to regulate the market. They establish the price based on historical usage data. The price are preknown to the users, encouraging them to shift the loads to lower price periods voluntarily to reduce the total load on the power grid at peak hours. In this paper, the two step high–low TOU pricing of the Ontario hydro (Canada) [9] is adopted as the wholesale price. Similar to the business model of a gas station, the charging operator charges the customers at a retail price, $\mathbf{Pr}_r = [Pr_r^1,\, Pr_r^2,\, \ldots,\, Pr_r^T]$. Normally, the retail price keeps flat during a business day.

## B. Design Objective

As the charging operator, the objective is to maximize the profit meanwhile to provide satisfactory services to the charging customers. In practical charging situations, owing to the constraints of charging service capability of the parking garage, vehicles' dynamic arrival and departure, and electricity price variation, it is inevitable to decline some customers' charging requirements. Without a proper scheduling of the charging activities, it may lead to a high task declining probability, thus severely affect the customers satisfaction and cause potential profit loss for the charging operator, which is unfavorable for both parties.

Denote $N_t$ as the accumulative total number of EVs arrived at the parking garage until time slot $t$. Each arrived vehicle is sequentially indexed. For the $i$th arrived EV, there is a binary decision variable $a_i(t)$ indicating its charging status at each time slot. Obviously, before the EV's arrival time $t_i^a$, after its departure time $t_i^d$, or in the case of its being rejected by the admission control mechanism, the decision variable $a_i(t)$ is 0. During the EV's sojourn time, the decision is made by the corresponding scheduling scheme of the CMS.

Considering the charging network service capability, at most $M$ EVs can be charged concurrently at the parking garage. Therefore, during each time slot the total number of EVs being charged should satisfy the following constraint:

$$\sum_{i=1}^{N_t} a_i(t) \leq M. \tag{2}$$

According to the admission control mechanism, not all the arrived EVs can be admitted for charging. However, for all the admitted ones, they must be guaranteed to reach their requested battery SOC before departure. Thus, for each of these admitted EVs, the accumulative charging duration $\Delta_i$ of charging the battery from $S_i^{\text{ini}}$ to $S_i^{\text{obj}}$ should satisfy the following constraint:

$$\Delta_i \leq t_i^d - t_i^a. \tag{3}$$

Detailed analysis of $\Delta_i$ is introduced in the battery charging characteristic analysis section.

Assume there are $N$ tasks arrived during the whole $T$ time slots. The task set of these $N$ tasks is denoted as $\boldsymbol{\mathcal{T}} = [\mathcal{T}_1, \ldots, \mathcal{T}_N]$. Based on the admission control mechanism, assume there are $N_d$ tasks declined for charging. Then, the task declining probability under the task $\boldsymbol{\mathcal{T}}$ scenario can be expressed as

$$P_d(\boldsymbol{\mathcal{T}}) = \frac{N_d}{N}. \tag{4}$$

The obtained profit for the charging operator is depended on the specific scheduling results, which can be further expressed as follows:

$$P_{rf}(\boldsymbol{\mathcal{T}})=\sum_{t=1}^{T}\sum_{i=1}^{N}\mathscr{P}\left(S_i\left(t\right)\right)\cdot\Delta t\cdot\left(Pr_r(t)-Pr_w(t)\right)\cdot a_i\left(t\right) \tag{5}$$

where $\mathscr{P}(S(t))$ is the charging power function following the battery charging characteristic. Therefore, the battery SOC of the charging EV can be updated as

$$S_i(t+1)=S_i(t)+\mathscr{P}(S_i(t))\cdot\Delta t\cdot a_i(t)/B. \tag{6}$$

Taking the interests of both the charging operator and the customers into account, a metric, utility, is proposed for the charging operator to comprehensively evaluate the charging scheduling performance. The utility function is expressed as

$$U(\boldsymbol{\mathcal{T}})=P_{rf}(\boldsymbol{\mathcal{T}})-\mathbb{C}(P_d(\boldsymbol{\mathcal{T}})) \tag{7}$$

where $P_{rf}(\boldsymbol{\mathcal{T}})$ and $P_d(\boldsymbol{\mathcal{T}})$ are the produced profit and task declining probability by a certain scheduling algorithm under the task set $\boldsymbol{\mathcal{T}}$ scenario. $\mathbb{C}(\cdot)$ is the cost function, describing the incurred profit loss for declining the customers' charging requirements. The parameters are set by the charging operator beforehand with the consideration of the maximum tolerated task declining probability. The ultimate objective for the charging operator is to achieve the maximum utility. Thus, one utility maximization problem is formulated as follows:

$$\begin{aligned}\max_{a_i(t)}\quad & U(\boldsymbol{\mathcal{T}})\\ \text{s.t.}\quad & \sum_{i=1}^{N_t}a_i(t)\le M,\ \forall t,\\ & \Delta_i\le t_i^d-t_i^a,\ \forall i,\\ & S_i(t+1)=S_i(t)+\mathscr{P}(S_i(t))\cdot\Delta t\cdot a_i(t)/B,\ \forall i,t.\end{aligned} \tag{8}$$

## IV. Battery Charging Characteristic Analysis

Most EVs on current market employ the Li-ion batteries, which have good performance on capacity, safety, life, and cost. Constant current-constant voltage (CC-CV) charging is the commonly used method for Li-ion battery charging [33]. However, due to the electrochemical characteristic of the EV battery, the charging current dramatically decreases along with the increase of battery SOC, which results in significant reduction of the charging power. This phenomenon also leads to a remarkable increase of the charging time to reach a higher SOC. All these unfavorable effects further impact the profitability of the charging operator.

We apply a simplified model to describe the relationship between the maximum allowable battery charging power and the battery SOC based on the Citroen C-Zero electric vehicle charging experimental measurements [34]. We consider all EVs equipped with the same kind of batteries with the same SOC change function $S(t)$. By applying the experimental results, a typical charging power function is expressed as

$$\mathscr{P}(S)=\begin{cases}P_0, & 0\le S\le S^{\text{th}},\\ \dfrac{1-S}{1-S^{\text{th}}}P_0, & S^{\text{th}}<S\le 1\end{cases} \tag{9}$$

where $S$ is the current battery SOC and $S^{\text{th}}$ is the threshold invoking a shift from the CC period to CV period. Since the voltage does not change much during the CC period, the charging power is simplified as a constant $P_0$. For the CV period, the charging power is simplified linearly decreasing with the growth of battery SOC.

The required charging duration for a particular task $i$ is mainly determined by its initial and requested battery SOCs, and the charging power. Based on the experimental measurements, to simplify the analysis, the initial battery SOC of each task directly determines the beginning charging power. Then, the charging duration for task $i$ can be obtained by the following Lemma.

*Lemma 1:* For any task $i$, given its initial and requested battery SOCs $S_i^{\text{ini}}$ and $S_i^{\text{req}}$, its required charging duration $\Delta_i$ can be obtained as

$$\Delta_i=\begin{cases}\frac{(S_i^{\text{req}}-S_i^{\text{ini}})B}{P_0}, & S_i^{\text{ini}}<S_i^{\text{req}}\le S_i^{\text{th}}\\ \frac{(S^{\text{th}}-S_i^{\text{ini}})B}{P_0}+\beta\ln(\frac{1-S^{\text{th}}}{1-S_i^{\text{req}}}), & S_i^{\text{ini}}\le S^{\text{th}}<S_i^{\text{req}}\\ \beta\ln(\frac{1-S_i^{\text{ini}}}{1-S_i^{\text{req}}}), & S^{\text{th}}\le S_i^{\text{ini}}<S_i^{\text{req}}\end{cases} \tag{10}$$

where $\beta=\frac{(1-S^{\text{th}})B}{P_0}$.

*Proof:* We consider all tasks follow the same SOC change function $S(t)$. For the CC period, as the charging power is a constant, the charging duration is determined by its initial battery SOC $S^{\text{ini}}$ and the CC-CV transition threshold $S^{\text{th}}$, which can be calculated as

$$\Delta^{cc}=\frac{\left(S^{\text{th}}-S^{\text{ini}}\right)\cdot B}{P_0} \tag{11}$$

where $B$ is the rated battery capacity. Then, the battery SOC changes with the CC period accumulative charging time can be expressed as

$$S^{cc}(t)=S^{\text{ini}}+\frac{P_0t}{B}. \tag{12}$$

For the CV period, the charging power linearly decreases with the increase of battery SOC. Assume that $\delta$ is a very small period, the SOC with the CV period accumulative charging time can be updated by

$$\begin{aligned}S^{cv}(t)&=S^{cv}(t-\delta)+P(t-\delta)\cdot\delta/B\\ &=S^{cv}(t-\delta)+(m-nS^{cv}(t-\delta))\cdot\delta\end{aligned} \tag{13}$$

where $m=n=\frac{P_0}{(1-S^{\text{th}})B}$. Then, a differential equation of $S$ can be obtained as

$$\dot{S^{cv}}(t)+nS^{cv}(t)-m=0. \tag{14}$$

By solving this differential equation, we can obtain a general solution for the change of battery SOC with the CV period accumulative charging time as

$$S^{cv}(t) = Ce^{-\frac{P_0}{(1-S^{\text{th}})B}t} + 1 \tag{15}$$

where $C$ is a constant. By applying the initial condition $S(0) = S^{\text{th}}$, the constant $C$ is determined as $C = S^{\text{th}} - 1$. Thus, we can obtain

$$S^{cv}(t) = (S^{\text{th}} - 1)e^{-\frac{P_0}{(1-S^{\text{th}})B}t} + 1. \tag{16}$$

Given each individual task's initial and requested battery SOCs, we can map these states to the SOC change function $S(t)$ and obtain its corresponding charging duration from $S^{\text{ini}}$ to $S^{\text{req}}$. The initial battery SOC of each task directly determines which charging period it begins. Then, for each individual task its battery charging characteristic can be analyzed as follows.

*Case 1*: $S^{\text{ini}} < S_i^{\text{req}} \le S^{\text{th}}$.

This kind of tasks' initial battery SOCs are very low and only require very few charging amount. The charging process only goes through the CC period. The battery charging power maintains at the maximum level, and the task's total charging duration can be expressed as $\Delta_i = \frac{(S_i^{\text{req}} - S_i^{\text{ini}})B}{P_0}$. Its battery SOC is linearly increasing as $S_i(t) = S_i^{\text{ini}} + \frac{P_0 t}{B}$.

*Case 2*: $S_i^{\text{int}} \le S^{\text{th}} < S_i^{\text{req}}$.

The charging process needs to go through both the CC and CV periods. For the CC period, the battery is charged from $S_i^{\text{ini}}$ to $S^{\text{th}}$. For the CV period, the battery is charged from $S^{\text{th}}$ to $S_i^{\text{req}}$. By mapping these states to the SOC change function $S(t)$, we can obtain this task's total charging duration, which is the summation of these two periods. Thus, it can be expressed as follows:

$$\begin{aligned}\Delta_i &= \Delta_i^{cc} + \Delta_i^{cv} \\ &= \frac{\left(S^{\text{th}} - S_i^{\text{ini}}\right) \cdot B}{P_0} + \frac{\left(1 - S^{\text{th}}\right)B}{P_0} \ln\left(\frac{1 - S^{\text{th}}}{1 - S_i^{\text{req}}}\right).\end{aligned} \tag{17}$$

Then, for this kind of tasks their battery SOCs at any accumulative charging time $t$ can be expressed as

$$S_i(t) = \begin{cases} S_i^{\text{ini}} + \frac{P_0 t}{B}, & t \le t_i^{cc}, \\ (S^{\text{th}} - 1)e^{-\frac{P_0}{(1-S^{\text{th}})B}(t - t_i^{cc})} + 1, & t > t_i^{cc} \end{cases} \tag{18}$$

where $t_i^{cc} = \frac{(S^{\text{th}} - S_i^{\text{ini}})B}{P_0}$ is the task's charging duration for the CC period.

*Case 3*: $S^{\text{th}} \le S_i^{\text{int}} < S_i^{\text{req}}$.

The charging process is deemed as only taking the CV period. Then, we can map its two battery SOC states $S_i^{\text{ini}}$ and $S_i^{\text{req}}$ to the SOC change function expressed in (16), and the charging duration is the time difference between these two states, which is expressed as

$$\Delta_i = \Delta_i^{cv} = \frac{\left(1 - S^{\text{th}}\right)B}{P_0} \ln\left(\frac{1 - S_i^{\text{ini}}}{1 - S_i^{\text{req}}}\right). \tag{19}$$

Then, for this kind of tasks their battery SOCs at any accumulative charging time $t$ can be expressed as

$$S_i(t) = (S^{\text{th}} - 1)e^{-\frac{P_0}{(1-S^{\text{th}})B}(t + t_i^{cv})} + 1 \tag{20}$$

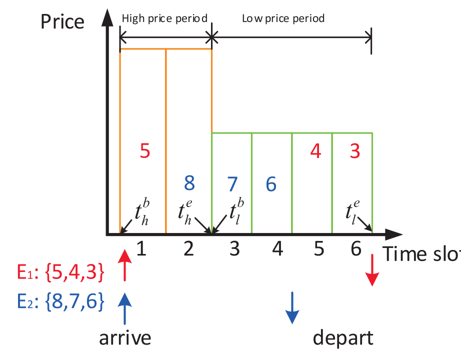



Fig. 2. Toy example.

where $t_i^{cv} = \frac{(1-S^{\text{th}})B}{P_0} \ln(\frac{1-S^{\text{th}}}{1-S_i^{\text{ini}}})$ is the duration following the SOC change function $S(t)$ with the SOC changing from $S^{\text{th}}$ to $S_i^{\text{ini}}$. ∎

According to Lemma 1, the charging amount $E_i(t)$ at each individual charging slot $t$ can be obtained by the SOC difference at the corresponding charging time. Given the required charging duration $\Delta_i$ of each task, its charging sequence $\mathbf{E_i}$ thus can be obtained. For different tasks, their charging sequences are heterogeneous. The charging activity at each slot cannot be treated equally and scheduled interchangeably.

One toy example to illustrate the impact of the battery charging characteristic on the scheduling is shown in Fig. 2. Assume the system capacity is 6 time slots, the first 2 time slots are within the high price (low profit) period, and the following 4 time slots belong to the low price (high profit) period. There are two tasks requiring charging services. Task 1 and 2 arrive at the beginning of the 1st time slot, and depart at the 6th and the 4th time slots, respectively. The charging sequences of these two tasks are denoted as $\mathbf{E}_1 = \{5, 4, 3\}$, and $\mathbf{E}_2 = \{8, 7, 6\}$. Each number is the amount of energy that can be charged to the EV in the particular slot given its initial SOC and follows the battery charging characteristic. For instance, the number "5" denotes that 5 kWh energy will be charged to EV 1 during its first charging time slot. The objective for the charging operator is to charge more energy at the low price period to earn more profit, meanwhile try its best to accommodate more tasks' charging requirements. To maximize the profit while satisfying all tasks charging requirements, we need to consider the issues of electricity price variations, all tasks' deadline restrictions and each task's charging power sequence decreasing trend. It can be noted that the new problem is more challenging than the counterpart with no battery charging characteristic consideration. Consequently, the charging operator must design efficient scheduling algorithm to achieve the desirable utility, which is discussed in detail in the subsequent sections.

## V. Admission Control and Scheduling Algorithms

In this section, the admission control mechanism is introduced to guarantee the service quality for all the EV charging customers. Then, the scheduling algorithms are designed to optimize the utility for the parking garage charging operator.

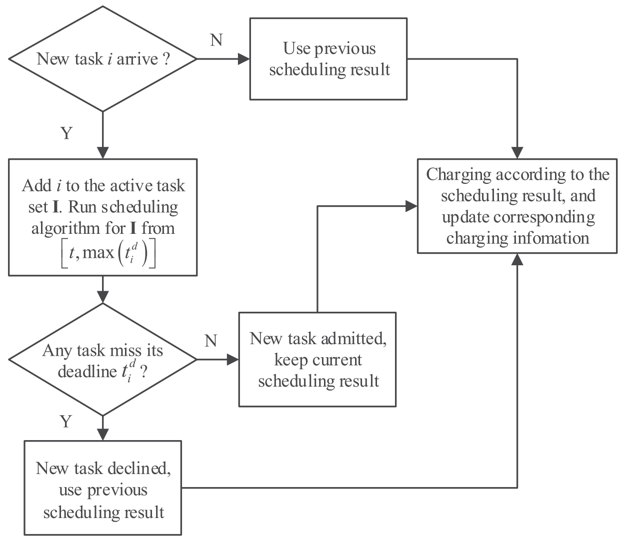



Fig. 3. Charging management system operation flow graph.

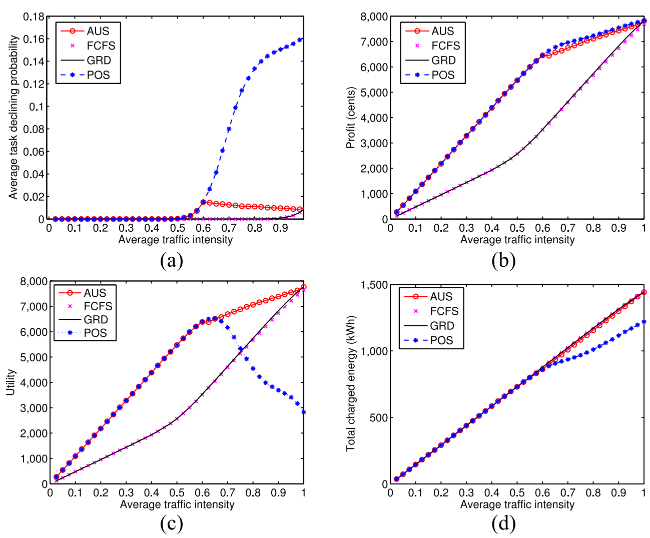



Fig. 4. Performance comparisons for Case 1: (a) Task declining probability. (b) Profit. (c) Utility. (d) Aggregated power.

## A. Admission Control Algorithm

To ensure the QoS for the EV charging customers, each admitted EV must be guaranteed to charge its battery to the requested SOC when it leaves the parking garage. The admission control mechanism can be viewed as a virtual scheduling procedure. Whenever a new task $i$ arrives, it will be put into an active scheduling task set $\mathbf{I}$ together with the existing admitted tasks. Then, all the tasks in $\mathbf{I}$ will be scheduled by the corresponding scheduling algorithm. Since each admitted task must achieve the requested SOC while departure, if any existing admitted task or the newly arrived task itself cannot be charged to its requested battery SOC at the departure, the new task should be declined of service; otherwise, it should be admitted. The flow graph of the charging management system is illustrated in Fig. 3. As the most important part of the charging management system, the scheduling algorithms are introduced in next section in detail.

## B. Scheduling Algorithm

The discussed EV charging scheduling problem is *causal* as the scheduling policy at each time slot $t$ depends only on the current information state $\mathbf{I_t}$. The future charging information is unknown for the charging operator beforehand, they cannot make a globally optimal scheduling. From [35], it can be seen that there does not exist a causal optimal scheduling policy. Since we cannot, in general, construct causal optimal scheduling policies, we must be content to design suboptimal heuristic scheduling algorithms.

Considering the time urgency and charging demand comprehensively, the most urgent tasks should have the highest priority to be scheduled. A metric, *flexibility* [35], is utilized to describe the urgency of each task, which is defined as follows.

*Definition 1:* The difference between the amount of remaining time to complete a task and the remaining unfinished charging requirement $L_i$ is defined as the flexibility of task $i$, denoted as $\Phi_i(t)$, satisfying

$$\Phi_i(t) = t_i^d - t - L_i(t). \tag{21}$$

Obviously, a greedy-based scheduling algorithm (GRD) can be applied to solve the problem. Larger flexibility factors imply greater load deferability. In particular, if a task is not flexible ($\Phi_i(t) = 0$), it must be served immediately to be completed by its deadline. Otherwise, the tasks with the minimum charging amount are sequentially scheduled for charging at each time slot during the high price period; the tasks with the maximum charging amount win the opportunity within the low price period. Apparently, the GRD scheduling algorithm has excellent task admission performance and resource utilization ratio. However, the electricity price variation trend is not taken into consideration. It cannot guarantee as much power as possible to be charged in the low price period. Thus the total profit, the most concerned part for the charging operator, cannot be maximized.

To mitigate the price insensibility of the GRD scheduling, a price oriented scheduling algorithm (POS), as depicted in Algorithm 1, is designed to improve the profit. The key process of POS algorithm is to schedule more high-power tasks in the low price period following the charging power causal decreasing characteristic. If the current time is within the low price period or the estimated total charging requirements is smaller than the low price period capacity, as shown in lines 8 and 15 of Algorithm 1, each round the task with the most charging energy amount wins the scheduling opportunity. Otherwise, as depicted in lines from 9 to 13, it preferentially schedules the charging requirements to the high-profit region until the high-profit region reaches its capacity limit. After this stage, it schedules the remaining charging requirements within the available low-profit region. The task with the least charging energy amount has the highest priority during this process. The POS algorithm is aggressive in increasing the profit. However, there is a drawback of it, i.e., the task declining probability cannot be guaranteed, especially for the high traffic intensity scenarios. Since the early arrived tasks always take up the lowest price slot in advance, the later arrived tasks may be blocked due to insufficient charging slots

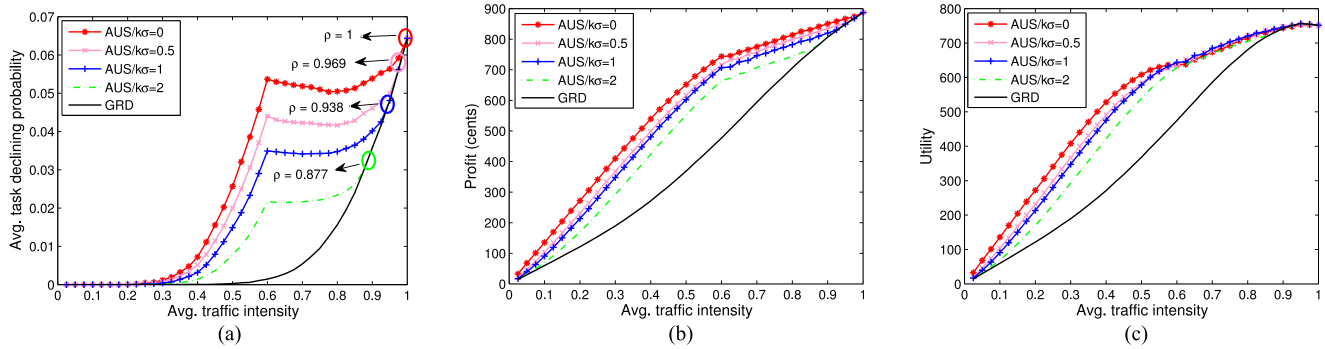



Fig. 5. Performance comparisons with different reservation amount: (a) Task declining probability. (b) Profit. (c) Utility.

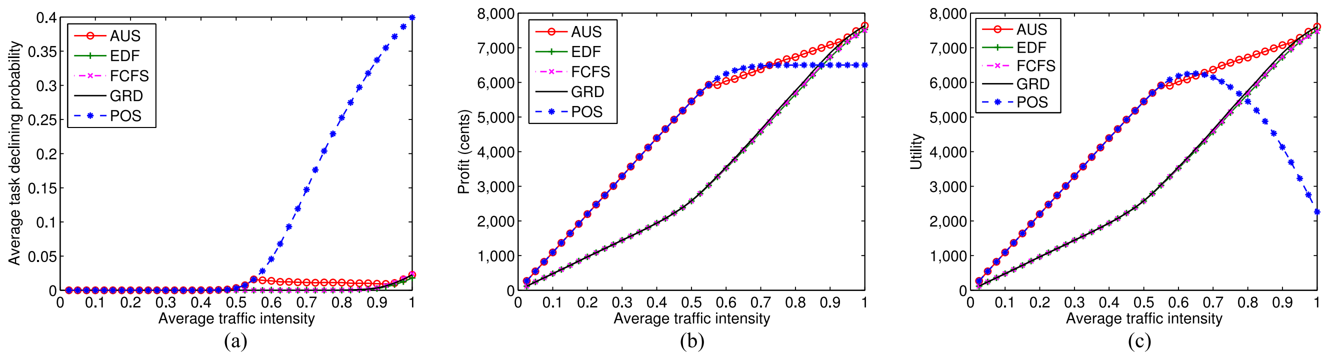



Fig. 6. Performance comparisons for Case 2: (a) Task declining probability. (b) Profit. (c) Utility.

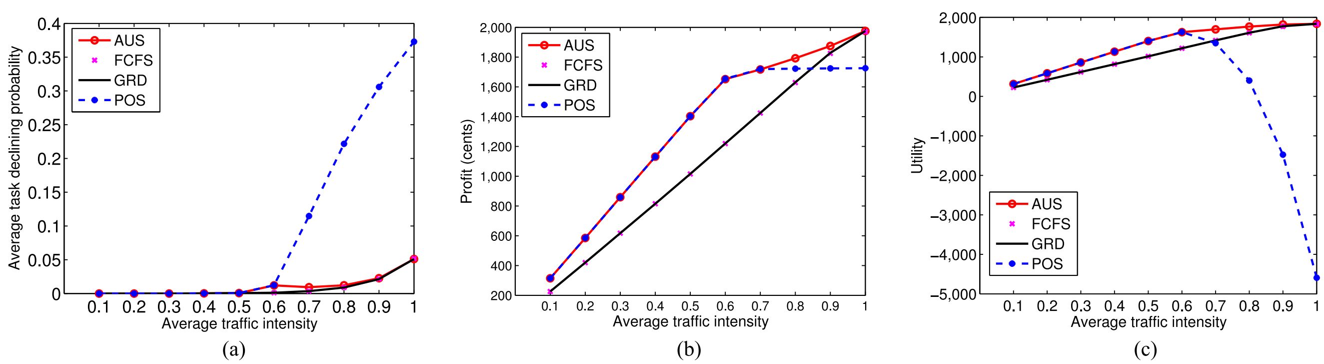



Fig. 7. Performance comparisons for vehicle stochastic arrivals: (a) Task declining probability. (b) Profit. (c) Utility.

available to them. It can be noticed that the two metrics, profit and task declining probability, cannot be guaranteed optimal at the same time.

Therefore, considering the effects of electricity price variation, charging power causal decreasing, and deadline constraints in a comprehensive manner, we propose an adaptive utility oriented scheduling algorithm (AUS) to achieve the desirable total utility for the charging operator. The AUS algorithm, as described in Algorithm 2, adaptively makes the decision on when to invoke each procedure based on the estimated incoming charging requirements. The estimation of the average total charging requirement $\bar{R}$ during a specified period $\alpha$ can be expressed as follows:

$$\bar{R} = \bar{\lambda} \cdot \alpha \cdot \bar{L} \tag{22}$$

where $\bar{\lambda}$ is the average arrival rate during the specified period $\alpha$, and $\bar{L}$ is the average charging slot number per EV. All the information can be estimated by historical data collected by the charging operator.

Depending on the TOU electricity pricing model, the service capacity of the two price periods can be expressed as

$$C_h = M \cdot (t_h^e - t_h^b), \tag{23}$$

$$C_l = M \cdot (t_d - t_l^b) \tag{24}$$

where the high price period ending time $t_h^e$ and the low price period beginning time $t_l^b$ are equal. It is possible that the price may change a few times during the day, and with a small extension of our proposed AUS algorithm, i.e., comparing the total charging requirements and the low price period capacity and

**Algorithm 1:** Price oriented scheduling algorithm.

**Input**: $M, t, \mathbf{S} = \{\mathbf{I}, \mathbf{L}, \mathbf{E}, \mathbf{t^d}\}, t_h^e$
**Output**: $\mathbf{A}$
**procedure** POS($M, t, \mathbf{S}, t_h^e$)
  **if** new task is admitted at $t$ **then**
    update $\mathbf{S}$, $t_D = \max(t_i^d), i \in \mathbf{I}$
    **if** $t \leq t_l^b$ **then**
      **if** $\sum_i L_i(t) \leq M(t_D - t_h^e)$ **then**
        $x = t_l^b$, SCHEDLP($k$) for $k$ from $[x, t_D]$
      **else**
        $\delta = \sum_i L_i(t) - M(t_D - t_h^e)$
        SCHEDHP($k$) for the $\delta$ requirements
        $x = t_l^b$, SCHEDLP($k$) for $k$ from $[x, t_D]$
      **end if**
    **else**
      $x = t$, SCHEDLP($k$) for $k$ from $[x, t_D]$
    **end if**
  **end if**
**end procedure**
**procedure** SCHEDHP($t$) / SCHEDLP($t$)
  **if** $\exists \Phi_j(t) = 0, j \in J$ **then**
    schedule all tasks in $J$ immediately
    update **S**, **A**
  **else**
    $N = \min\{|I|, M, M - |J|\}$
    SCHEDHP: schedule the $N$ tasks with min $E(t)$
    SCHEDLP: schedule the $N$ tasks with max $E(t)$
    update **S**, **A**
  **end if**
**end procedure**

**Algorithm 2:** Adaptive utility oriented scheduling algorithm.

**Input**: $M, \mathbf{S}, t_h^b, t_h^e, t_d$
**Output**: $\mathbf{A}$
**procedure** AUS($M, \mathbf{S}, t_h^b, t_h^e, t_d$)
  estimate $\bar{R}$ for $[t_h^b, t_d]$ with (22)
  calculate $C_l$ with (24)
  $\Theta = \max\{\bar{R} - C_l + \theta, 0\}$
  schedule with GRD for the first $\Theta$ requirements
  schedule with POS for all the remaining requirements
**end procedure**

adjust the scheduling sequence, we can still handle the changed price model effectively.

### C. Discussion

For the proposed AUS algorithm, utilizing the GRD scheduling at the beginning guarantees a low task declining probability, and the subsequent POS scheduling guarantees the desirable profit. Since the arrivals of the tasks are random in real scenarios, the actual arrived vehicle number has some deviation from the estimated arrived vehicle number. For the underestimation case, i.e., $\sum_i L_i > \bar{R}$, the underestimation of the total incoming requirements may cause a high task declining probability and then decrease the total utility for the charging operator. To avoid the performance degradation, the robustness issue of the algorithm is considered by incorporating the reservation mechanism. The charging operator can reserve $\theta$ extra high-price slots to achieve a relatively small task declining probability and meanwhile a satisfactory profit to guarantee a desirable utility. The extra reservation amount $\theta$ can be set as $\theta = k\sigma\bar{L}$, and $\theta \leq C_s - \bar{R}$, where $\sigma$ is the standard deviation of the arrived vehicle number, $k$ is a tuning parameter, and $C_s$ is the system capacity. Increasing $\theta$ makes the scheduling more conservative and secure, so the task declining probability can be substantially decreased. Whereas, the profit is probably affected. Because more will be charged in the high price period and less can be selected in the low price period, sometimes even cannot fully utilize the low price period. By analyzing the AUS algorithm, we can find that it converges to the GRD algorithm when the estimated average total charging requirement reaches the system capacity. Consequently, the specific average traffic intensity $\rho$ at which the AUS algorithm converges to the GRD algorithm with given reservation amount $\theta$ can be estimated by the following equation:

$$\rho = 1 - \frac{\theta}{C_s}. \tag{25}$$

Thus, the charging operator can obtain the desired task declining probability by adjusting the reservation amount.

## VI. Case Studies

### A. Simulation Settings

Take a workplace parking garage charging station as an instance to study the charging strategy. With each slot duration $\Delta t = 1$ min, one business day (7 am–5 pm) is equally divided into $T = 600$ time slots. Considering the current EV penetration rate, traffic pattern and typical power configuration in a workplace parking garage, 8 EVs can be charged concurrently [36]. The whole $T$ time slots are divided into three periods with different arrival rates (7 am–9 am, 10$\lambda$; 9 am–12 pm, 2$\lambda$; 12 pm–4 pm, 0.5$\lambda$). Two charging cases are considered as examples: Case 1, by the default setting of the charging station, all EVs depart at the end of the business day; Case 2, the EVs depart randomly around the peak off-work hours following a truncated Gaussian distribution $\mathcal{N}$(4:30 pm, $\sqrt{30}$ mins), and $t_i^a < t_i^d \leq$ 5 pm. The Citroen C-Zero with 16 kWh battery is investigated. Based on the study of the EV user charging behavior [32], the initial EV battery SOC of a recharge cycle is assumed to follow the truncated Gaussian distribution $\mathcal{N}(0.1, 0.2)$, and $0 \leq S_i^{\text{ini}} <$ 0.9. The battery CC-CV stage transition threshold is 0.6. The required SOCs of all charged batteries are preferred as 0.9. The flat retail charging price for the customers is 20 cents/kWh, and the wholesale price adopts the 2015 winter TOU price of Ontario Hydro [9] with high price as 17.5 cents/kWh and low price as 12.8 cents/kWh.

### B. Analysis and Comparison of Results

To better analyze the performance of the proposed adaptive utility oriented scheduling (AUS), the greedy scheduling (GRD), profit oriented scheduling (POS), and most EV charging stations currently adopted first come first serve scheduling (FCFS) are taken for comparisons under 1000 Monte Carlo simulations. For Case 2, another widely utilized charging strategy earliest deadline first (EDF) is considered as well.

Two key performance indexes profit and task declining probability are first investigated for Case 1 under the different traffic intensity scenarios, as shown in Fig. 4(a) and (b), respectively. Task declining probability affects the customer satisfaction, and profit is the motivation for the charging operator. However, it can be seen that the two performance indexes cannot be guaranteed optimal at the same time for any scheduling strategy. Although the main objective for the charging operator is to obtain the maximum profit. It is quite undesirable for the charging station to have a large task declining probability, which severely affects its service reputation and leads to great potential profit loss. Thus, by taking the interests of both parties into account, we compare the utility of each algorithm to comprehensively evaluate the scheduling performance in Fig. 4(c). The cost function here is set as $\mathbb{C}(P_d) = a \cdot (e^{b \cdot P_d} - 1)$ by the charging operator, where $a = 200$, and $b = 20$. The aggregated power demands of the charging station during the whole business day are compared in Fig. 4(d) as well to reflect the energy utilization.

From the simulation results, it can be noted that the GRD algorithm achieves the lowest task declining probability among all algorithms, but losses a lot of profit. The POS algorithm aggressively increases the profit, but the task declining probability is quite unacceptable. By contrast, the proposed AUS charging strategy is sophisticated to achieve the maximum utility with considerable profit under the premise of a relatively low task declining probability. In addition, the AUS algorithm can obtain more profit compared with the high resource utilization algorithms GRD and FCFS, and meanwhile ensure a low task declining probability compared with the POS algorithm. The energy utilization ratio is also promising among all scheduling algorithms, which makes the AUS algorithm the best choice for the parking garage charging operator.

The charging operator can also adopt the introduced reservation mechanism of the AUS algorithm to mitigate the performance degradation caused by the charging information mismatching with vehicle stochastic arrivals. Take the simplest single charger case as illustration. The effects on the scheduling performance with different reservation amounts are compared in Fig. 5. Same as the previous analysis, reserving more high-price period resources could effectively decrease the task declining probability under different traffic intensity cases. With the increase of average traffic intensity the AUS algorithm gradually converges to the GRD algorithm, the converging points obtained from the simulation results are in good match with the theoretical results, as shown in Fig. 5(a). Fig. 5(b) shows the profit comparison under different reservation amount cases, and it can be observed that reserving more high-price period resources results in some profit loss. However, choosing the proper reservation amount can achieve a desirable utility, as shown in Fig. 5(c). With $k\sigma = 1$, it effectively decreases the task declining probability and also obtains the best utility, which is promising for both the customers and the charging operator. Consequently, the garage charging operator can always achieve the desirable utility by choosing a proper reservation amount under different cases.

For Case 2, the vehicles' mobility pattern is more complicated. Deadline restricted scheduling is considered in this case. We also evaluate the different performance to demonstrate the effectiveness of the proposed AUS algorithm. As depicted in Fig. 6, we can find that the proposed AUS algorithm is robust to achieve the best utility under the dynamic departure scenario. The task declining probability is properly controlled under different traffic intensity cases, which well guarantees the interests of customers. Meanwhile, the promising profit for the charging operator can also be obtained. Thus, it can provide effective guidance for the garage charging operator to make proper scheduling for the incoming charging requirements, thereby to achieve the desirable utility. The reservation mechanism is also applied under this scenario. Due to the page limit, detailed discussions are omitted here.

To demonstrate the vehicle mobility pattern independence of our proposed AUS scheduling algorithm, we consider the scenarios where EVs uniformly arrive at the parking garage for a simple two-charger scenario. The performance of task declining probability, obtained profit, and achieved total utility with different scheduling algorithms under different traffic scenarios are compared in Fig. 7. From the simulation results, it can be seen that the proposed AUS algorithm still achieves the maximum utility with considerable profit gain under the premise of a relatively low task declining probability. Consequently, our proposed scheduling algorithm is applicable under different stochastic vehicle mobility models.

## VII. Conclusion

In this paper, we investigated the EV charging problem at an intelligent parking garage subject to the real TOU electricity pricing. We designed a multicharging system for the garage charging operator to effectively provide charging services by jointly considering the charging station profit and customer satisfaction. Besides, we analyzed the battery charging characteristic change during the actual charging process and applied it into the EV charging problem. Furthermore, we proposed an adaptive utility oriented scheduling algorithm to effectively achieve the maximum total utility for the charging operator under the dynamic traffic pattern scenario. We also discussed the reservation mechanism for the charging operator to mitigate the performance degradation caused by the charging information mismatching with vehicles' stochastic arrivals. Through extensive simulations, it has been shown that the proposed AUS algorithm is applicable under different stochastic vehicle mobility processes. With it, the charging operator can achieve the best performance compared with other existing algorithms, which is promising for the parking garage charging service proliferation. Given the promising direction, there are many issues to be further studied in our future work. Inspiring by the discussions of Markov process in [37] and [38], we can consider the Markovian property of the arrival process to further extend our work and utilize the M/G/K queue to analyze the charging process. How to schedule the charging activity according to different pricing schemes and how to integrate the incentive mechanism to achieve a win-win solution for both the customers and the charging operator are some further directions for us to consider.

## References


[1] 2016. [Online]. Available: https://www.iea.org/publications/freepublications/publication/Global_EV_Outlook_2016.pdf.

[2] I. S. Bayram, G. Michailidis, and M. Devetsikiotis, "Electric power resource provisioning for large scale public EV charging facilities," in *Proc. IEEE Int. Conf. Smart Grid Commun.*, 2013, pp. 133–138.

[3] Y.-M. Wi, J.-U. Lee, and S.-K. Joo, "Electric vehicle charging method for smart homes/buildings with a photovoltaic system," *IEEE Trans. Consum. Electron.*, vol. 59, no. 2, pp. 323–328, May 2013.

[4] T. Ma and O. A. Mohammed, "Optimal charging of plug-in electric vehicles for a car-park infrastructure," *IEEE Trans. Ind. Appl.*, vol. 50, no. 4, pp. 2323–2330, Jul. 2014.

[5] Z. Wei, J. He, M. Xing, and L. Cai, "Utility maximization for electric vehicle charging with admission control and scheduling," in *Proc. IEEE Int. Conf. Commun.*, 2015, pp. 661–666.

[6] S. Chen, L. Tong, and T. He, "Optimal deadline scheduling with commitment," in *Proc. Annu. Allerton Conf. Commun., Control, Comput.*, 2011, pp. 111–118.

[7] Y. Cao *et al.*, "An optimized EV charging model considering TOU price and SOC curve," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 388–393, Mar. 2012.

[8] J. Dong, G. Xue, and R. Li, "Demand response in China: Regulations, pilot projects and recommendations–A review," *Renewable Sustain. Energy Rev.*, vol. 59, pp. 13–27, 2016.

[9] 2015. [Online]. Available: http://www.ontarioenergyboard.ca/OEB/Consumers/Electricity/Electricity+Prices.

[10] K. Onda, T. Ohshima, M. Nakayama, K. Fukuda, and T. Araki, "Thermal behavior of small lithium-ion battery during rapid charge and discharge cycles," *J. Power Sources*, vol. 158, no. 1, pp. 535–542, 2006.

[11] Q. Wang, X. Liu, J. Du, and F. Kong, "Smart charging for electric vehicles: A survey from the algorithmic perspective," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1500–1517, Apr.–Jun. 2016.

[12] Q. Chen, N. Liu, C. Wang, and J. Zhang, "Optimal power utilizing strategy for PV-based EV charging stations considering real-time price," in *Proc. IEEE Conf. Expo Transp. Electrific. Asia-Pac.*, 2014, pp. 1–6.

[13] N. Liu *et al.*, "A heuristic operation strategy for commercial building microgrids containing EVs and PV system," *IEEE Trans. Ind. Electron*, vol. 62, no. 4, pp. 2560–2570, Apr. 2015.

[14] N. Liu, Q. Chen, X. Lu, J. Liu, and J. Zhang, "A charging strategy for PV-based battery switch stations considering service availability and self-consumption of PV energy," *IEEE Trans. Ind. Electron*, vol. 62, no. 8, pp. 4878–4889, Aug. 2015.

[15] L. Jian, H. Xue, G. Xu, X. Zhu, D. Zhao, and Z. Shao, "Regulated charging of plug-in hybrid electric vehicles for minimizing load variance in household smart microgrid," *IEEE Trans. Ind. Electron*, vol. 60, no. 8, pp. 3218–3226, Aug. 2013.

[16] L. Yang, J. Zhang, and H. V. Poor, "Risk-aware day-ahead scheduling and real-time dispatch for electric vehicle charging," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 693–702, Mar. 2014.

[17] W. Tang, S. Bi, and Y. J. A. Zhang, "Online coordinated charging decision algorithm for electric vehicles without future information," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2810–2824, Nov. 2014.

[18] D. Said, S. Cherkaoui, and L. Khoukhi, "Scheduling protocol with load management for EV charging," in *Proc. IEEE Global Commun. Conf.*, 2014, pp. 362–367.

[19] Z. Wei, J. He, and L. Cai, "Admission control and scheduling for EV charging station considering time-of-use pricing," in *Proc. IEEE Veh. Technol. Conf.*, 2016, pp. 1–5.

[20] T. Zhang, W. Chen, Z. Han, and Z. Cao, "Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price," *IEEE Trans. Veh. Technol.*, vol. 63, no. 6, pp. 2600–2612, Jul. 2014.

[21] H.-J. Kim, J. Lee, G.-L. Park, M.-J. Kang, and M. Kang, "An efficient scheduling scheme on charging stations for smart transportation," in *Security-Enriched Urban Computing and Smart Grid*. Berlin, Germany: Springer, 2010, pp. 274–278.

[22] I. S. Bayram, G. Michailidis, M. Devetsikiotis, and F. Granelli, "Electric power allocation in a network of fast charging stations," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1235–1246, Jul. 2013.

[23] H. Li, X. Jing, and H. R. Karimi, "Output-feedback-based $h_\infty$ control for vehicle suspension systems with control delay," *IEEE Trans. Ind. Electron*, vol. 61, no. 1, pp. 436–446, Jan. 2014.

[24] S. Chen, Y. Ji, and L. Tong, "Large scale charging of electric vehicles," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, 2012, pp. 1–9.

[25] S. Chen, Y. Ji, and L. Tong, "Deadline scheduling for large scale charging of electric vehicles with renewable energy," in *Proc. IEEE 7th Sensor Array Multichannel Signal Process. Workshop*, 2012, pp. 13–16.

[26] H. Qin and W. Zhang, "Charging scheduling with minimal waiting in a network of electric vehicles and charging stations," in *Proc. 8th ACM Int. Workshop Veh. Inter-Netw.*, 2011, pp. 51–60.

[27] P. Fan, B. Sainbayar, and S. Ren, "Operation analysis of fast charging stations with energy demand control of electric vehicles," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1819–1826, Jul. 2015.

[28] M. Ş. Kuran, A. C. Viana, L. Iannone, D. Kofman, G. Mermoud, and J. P. Vasseur, "A smart parking lot management system for scheduling the recharging of electric vehicles," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2942–2953, Nov. 2015.

[29] A. Ovalle, A. Hably, S. Bacha, G. Ramos, and J. Hossain, "Escort evolutionary game dynamics approach for integral load management of electric vehicle fleets," *IEEE Trans. Ind. Electron*, vol. 64, no. 2, pp. 1358–1369, Feb. 2017.

[30] W. Tang and Y. J. A. Zhang, "A model predictive control approach for low-complexity electric vehicle charging scheduling: Optimality and scalability," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1050–1063, 2017.

[31] F. Soares, P. R. Almeida, and J. P. Lopes, "Quasi-real-time management of electric vehicles charging," *Elect. Power Syst. Res.*, vol. 108, pp. 293–303, 2014.

[32] T. Franke and J. F. Krems, "Understanding charging behaviour of electric vehicle users," *Transport. Res. Part F, Traffic Psychol. Behav.*, vol. 21, pp. 75–89, 2013.

[33] P. Palensky, E. Widl, M. Stifter, and A. Elsheikh, "Modeling intelligent energy systems: Co-simulation platform for validating flexible-demand EV charging management," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1939–1947, Dec 2013.

[34] D. Andersson and D. Carlsson, "Measurement of ABB's prototype fast charging station for electric vehicles," Master's thesis, Chalmers Univ. Technol., Gothenburg, Sweden, 2012.

[35] A. Subramanian, M. Garcia, A. Dominguez-Garcia, D. Callaway, K. Poolla, and P. Varaiya, "Real-time scheduling of deferrable electric loads," in *Proc. Amer. Control Conf.*, 2012, pp. 3643–3650.

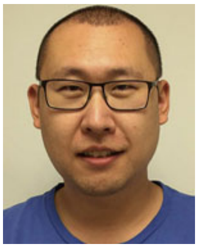
[36] 2016. [Online]. Available: https://www.tesla.com/en_CA/supercharger

[37] Y. Wei, J. Qiu, H. R. Karimi, and M. Wang, "New results on $\mathscr{H}_\infty$ dynamic output feedback control for markovian jump systems with time-varying delay and defective mode information," *Opt. Control Appl. Methods*, vol. 35, no. 6, pp. 656–675, 2014.

[38] Y. Wei, J. Qiu, and H. R. Karimi, "Quantized $\mathscr{H}_\infty$ filtering for continuous-time markovian jump systems with deficient mode information," *Asian J. Control*, vol. 17, no. 5, pp. 1914–1923, 2015.

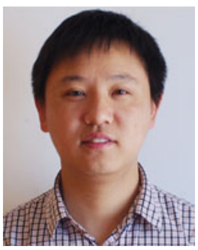

**Zhe Wei** (S'15) received the B.Sc. and M.Sc. degrees in electrical engineering from Northwestern Polytechnical University, Xi'an, China, in 2009 and 2012, respectively. He is currently working toward the Ph.D. degree in electrical engineering at the Department of Electrical and Computer Engineering, University of Victoria, Victoria, BC, Canada.

His research interests include electric vehicle charging scheduling, resource allocation, smart grid, and demand response.



**Yue Li** received the B.Sc. and M.Sc. degrees in electrical engineering from the Beijing Institute of Technology, Beijing, China, in 2006 and 2008, respectively. He is currently working toward the Ph.D. degree in electrical engineering at the Department of Electrical and Computer Engineering, University of Victoria, Victoria, BC, Canada.

During 2008–2013, he worked for Huawei as a standard preresearch Engineer in the Department of Wireless Research. He has been closely involved in 3GPP standards' evolvement and held numerous patents in WCMDA, LTE-A, and 5G systems. His research interests include next-generation cellular system, wireless network design and optimization, wireless system modeling, and performance analysis.



**Yongmin Zhang** (S'12–M'15) received the Ph.D. degree in control science and engineering from Zhejiang University, Hangzhou, China, in 2015.

He is currently a Postdoctoral Research Fellow in both the State Key Laboratory of Industrial Control Technology at Zhejiang University and the Department of Electrical and Computer Engineering, University of Victoria, Victoria, BC, Canada. His research interests include wireless sensor networks, resource management and optimization, and smart grid.

**Lin Cai** (S'00–M'06–SM'10) received the M.A.Sc. and Ph.D. degrees in electrical and computer engineering from the University of Waterloo, Waterloo, ON, Canada, in 2002 and 2005, respectively.

Since 2005, she has been with the Department of Electrical and Computer Engineering, University of Victoria, Victoria, BC, Canada, where she is currently a Professor. Her research interests include areas in communications and networking, with a focus on network protocol and architecture design supporting emerging multimedia traffic over wireless, mobile, *ad hoc*, and sensor networks.

Prof. Cai received the NSERC Discovery Accelerator Supplement Grants in 2010 and 2015, respectively, and the best paper awards of IEEE International Conference on Communications 2008 and IEEE Wireless Communications and Networking Conference 2011. She has served as a TPC symposium cochair for IEEE Globecom 2010 and Globecom 2013, an Associate Editor for IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, *EURASIP Journal on Wireless Communications and Networking*, *International Journal of Sensor Networks*, and *Journal of Communications and Networks*, and a Distinguished Lecturer of IEEE VTS society.