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Dynamic Charging Scheduling for EV Parking Lots With Photovoltaic Power System

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ABSTRACT This paper studies the optimal charging scheduling for electric vehicles (EVs) in a workplace parking lot, powered by both the photovoltaic power system and the power grid. Due to the uncertainty and fluctuation of solar energy and the time-varying EV charging requirements, it is challenging to guarantee the economic operation of the parking lot charging station. To address this issue, we formulate the EV charging scheduling in the parking lot as a benefit maximization problem. First, by analyzing the relationship among the EV charging requirements, the charging load, and the harvested solar energy, we derive several necessary conditions for obtaining an optimal decision, such that the primal optimization problem can be simplified. Then, we design a dynamic charging scheduling scheme (DCSS) to manage the EV charging processes, in which the model predictive control method is employed to deal with the real-time information of EV charging requirements and the solar energy. Simulation results demonstrate the effectiveness and efficiency of the designed DCSS.

INDEX TERMS Electric vehicle, charging scheduling, photovoltaic power, model predictive control.

NOMENCLATURE

t	The t-th time slot.
$\bar{t}$	The current time slot.
t'	An upcoming time slot in the time period.
$x_{i,t}$	Charging decision of EV i during time slot t.
$\hat{x}_{i,t}$	Maximal charging duration for EV i during time slot t.
λ_t	Total number of EVs that arrive at the parking lot during time slot t.
A_i	Arrival time of EV i at the parking lot.
$C_T^{\bar{t}}$	Total expected benefit of the parking lot during time slot $\bar{t}$ to T.
C_t^G	The electricity cost of the parking lot during time slot t.
D_i	Departure time of EV i at the parking lot.
E_t^R	Total amount of the harvested solar energy during time slot t.
E_t^{R0}	Total amount of the unused solar energy during time slot t.
E_t^G	Total amount of the energy that from the power grid during time slot t.
E_D	The expected energy consumption per kilometer of EV.
$E_{i,t}$	The amount of energy that is charged to EV i during time slot t.
$\bar{E}_t$	Total charging load of the parking lot during time slot t.
$\bar{E}_t^{\max}$	The maximal charging load of the parking lot during time slot t.
$\hat{E}_{t'}^R$	The estimated value of E_t^R during upcoming time slot t'.
$\mathbb{I}$	The set of EVs that are charged in the parking lot during the entire time period.
$\bar{\mathbb{I}}(t)$	The set of EVs that are connected to the charging system at time slot t.
M_t^A	The number of EVs that arrive at the parking lot during time slot t.
M_t^D	The number of EVs that leave the parking lot during time slot t.
$\bar{P}$	Charging power of one charging pile during each time slot.
R_i^t	The charging requirement of EV i during time slot t.

R_i^O Total charging requirement of EV i.
$R_{\mathbb{I}}^{\bar{t}}$ The total amount of the EV charging requirements during the remainder time period at current time slot $\bar{t}$.
T Total amount of time slots in one time period.

I. INTRODUCTION

Climate change and extreme weather, highly related to the Greenhouse Gases (GHGs) emission, have been a critical issue facing the world. Recent data show that transportation and electricity generation, two of the major contributors to the GHGs, have an increasing trend [1]. Electric Vehicles (EVs) are a key to promote the sustainable energy development and address the air quality and climate change issues. Solar energy is green and renewable, so using Photovoltaic Power (PV) to charge EVs is promising, especially for the workplace parking lots thanks to their large space for installing the PV system and long available daytime for EVs to be charged [2].

Using solar energy solely may not satisfy the EV charging requirements due to its fluctuations and limited quantities. To satisfy the EV charging requirements, the combination of the solar energy and the power grid, namely the PV–Grid, becomes prominent [3]. The economic operation objective of the parking lot charging station is to maximize the utilization of solar energy given its low cost and smooth the load on the power grid to avoid the peak load penalty. However, the time-varying EV charging requirements and the fluctuated solar energy make the management of charging processes more difficult. That is because an aggressive charging scheduling scheme tries to finish all charging tasks earlier and may lead to a low utilization of the solar energy, while a conservative one may delay a large number of charging requirements until the last minutes and increase the peak load on the power grid. It is necessary to design an optimal charging scheduling scheme based on the realtime information of the EV charging requirements and the solar energy [4].

The charging scheduling problems with various goals for the charging system, powered by the power grid with or without renewable energy sources, have been widely studied [5], such as reducing the cost and guaranteeing system stability [6]–[8], maximizing total benefit [9]–[12], smoothing the charging load on the power grid [13]–[15], improving operation efficiency [16]–[18], and other objectives [19]–[21]. These solutions are typically based on a combination of the current data and the estimated data in future. Given the highly dynamic EV charging requirements and intermittent renewable energy sources, how to optimize the scheduler to respond quickly to realtime information remains an open and critical issue.

To deal with the challenge, Model Predictive Control (MPC) has been used to design the charging scheduling scheme since MPC allows the current time slot to be optimized while keeping future time slots in account. In this paper, based on the realtime information at current time slot and estimated information in the upcoming time slots, a dynamic model has been proposed to update the EV charging requirements and the energy supply of the parking lot. Then, a benefit maximization problem is formulated to maximize the total benefit of the parking lot. We derive several necessary conditions for the optimal solution to simplify the primal problem. To handle the time-varying solar energy and EV charging requirements, we proposed a MPC-based distributed scheme to solve the charging scheduling problem. The contributions of this paper are summarized as follows:

- We formulated the charging scheduling for a workplace parking lot, powered by both the PV system and the power grid, as a benefit maximization problem.
- We analyzed the relationship among the EV charging requirements, the charging load on the power grid, and that on the solar energy, and derived several necessary conditions for the optimal solution to simplify the primal problem.
- We proposed a Dynamic Charging Scheduling Scheme (DCSS) based on MPC to manage the EV charging processes to maximize the benefit of the parking lot.

The rest of the paper is organized as follows. Section II introduces the related works. Section III presents the system model and the problem formulation. Section IV derives several necessary conditions for the optimal solution. A DCSS is proposed in Section V. Section VI presents the performance analysis, followed by the concluding remarks and further research issues in Section VII.

II. RELATED WORKS

According to the optimized objectives, EV charging scheduling research can be classified into two categories: cost-aware charging scheduling schemes and efficiency-aware charging scheduling schemes.

A. COST-AWARE CHARGING SCHEDULING SCHEMES

Mohamed *et al.* [6] designed a fuzzy controller to manage the charging processes of EVs to reduce the overall daily cost and mitigate their impact on the power grid. Tushar *et al.* [7] proposed a classification scheme of EVs, such that the PV driven charging station can trade with different energy entities to reduce its total energy cost. Under the Time of Use (TOU) price, Liang *et al.* [8] studied the charging/discharging scheme in Vehicle-to-Grid (V2G) system and obtained a state-dependent policy to minimize the charging cost for individual EVs. Considering the battery characteristic and TOU price, Wei *et al.* [9] designed an intelligent charging management mechanism to maximize the interests of both the customers and the charging operator. Considering unpredictable EVs patterns and EV various charging preferences, Wang *et al.* [10] designed a Hybrid Centralized-Decentralized (HCD) charging control scheme for EVs to coordinate the EV charging processes, such that the revenues of the whole charging system can be maximized. Kim *et al.* [11] developed an algorithm to find the optimal charging scheduling, service pricing and energy storage scheme, such that the profit of charging stations can be maximized. Jin *et al.* [12] presented a Lyapunov optimization for EV charging scheduling problems to maximize the utilization of renewable energy and reduce total charging cost. These works typically assumed that the EV charging requirements or the renewable energy can be estimated and do not consider the realtime EV charging requirements and renewable energy.

B. EFFICIENCY-AWARE CHARGING SCHEDULING SCHEMES

Zhou *et al.* [13] achieved the Demand Side Management (DSM) by scheduling intelligent EV charging to relieve the power grid pressure. Wang *et al.* [14] designed a novel Two-stage EV charging mechanism to determine the energy generation and charging strategy dynamically, such that the peak-to-average ratio (PAR) and the energy cost can be reduced. Liu *et al.* [15] proposed a leader-follower game model between the EV owners and the distribution service provider, and then designed an optimal pricing based EV charging scheduling scheme to avoid system peak load. Zhang *et al.* [16] proposed a Markov Decision Process (MDP) based charging scheduling scheme to minimize the mean waiting time for EVs. Wang *et al.* [17] proposed a mobility-aware coordinated charging strategy for EVs in VANET-Enhanced Smart Grid, which can improve the overall energy utilization, avoid power system overloading, and can address the range anxieties of individual EVs. Farzin *et al.* [18] developed a novel framework based on the non-sequential Monte Carlo simulation method to quantify the potential contribution of parking lots to the reliability of PV–Grid charging systems. Yang *et al.* [20] proposed a risk-aware day-ahead scheduling and realtime dispatch algorithm to minimize the EV charging cost and the risk of the load mismatch. Lee *et al.* [21] took the competition with neighboring EV charging stations with renewable energy sources into account using game theory, and proved that there exists a unique pure Nash equilibrium for best response algorithms with arbitrary initial policy. These works mainly focused on operational efficiency of charging systems and the utilization of renewable energy in long-term, rather than the realtime benefit of the parking lot. Also, they lack the quick response abilities to the realtime changing information.

III. SYSTEM MODEL AND PROBLEM FORMULATION

Considering a workplace parking lot for a company, whose office hours are given, e.g., from 8:00am to 5:00pm. There are N charging piles with the AC level II charging mode in the parking lot. Each charging pile connects to the power bus of the parking lot with a centralized-controller-managed switch, such that the charging process of each EV can be managed by the controller. The power bus can be powered by both its internal PV system and the power grid. In this system, the central controller can not only collect/estimate the information of the PV system, the power grid and EVs, but also manage the charging processes of all the EVs by toggling the switches. The system model is shown in Fig. 1. Note that,

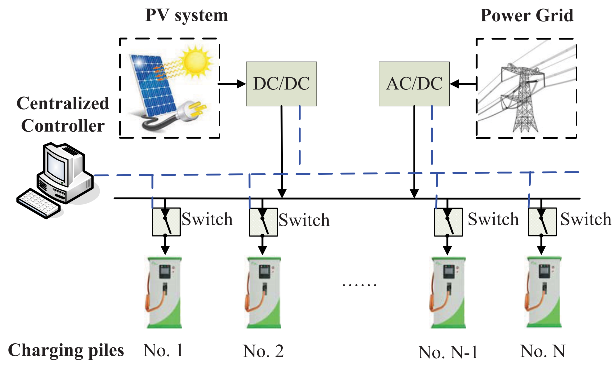


FIGURE 1. The operation model of the designed system.

the solar energy collected by the PV system can only be used by the parking lot since it cannot be fed back to the power grid due to stability and safety concerns.

In the following parts, we first introduce the models of charging processes, EV charging requirements, energy supplement, and operation requirements of the parking lot. Then, we formulate a benefit maximization problem to schedule the charging processes of EVs in the parking lot.

A. CHARGING MODEL OF THE PARKING LOT

Let one day be a time period, which can be divided into T time slots. Let $\bar{t}$ denote the current time slot and t' denote an upcoming time slot in the time period, respectively. Hence, $t' > \bar{t}$ always holds in this paper. Let $x_{i,t}$ denote the charging decision of EV i during time slot t, $t \in [\bar{t}, T]$, which is decided by the central controller. Here, the charging decision $x_{i,t}$ of EV i satisfies

$$0 \leq x_{i,t} \leq 1, \quad \forall t, \tag{1}$$

and the total amount of energy $E_{i,t}$ that is charged to EV i during time slot t is

$$E_{i,t} = x_{i,t}\bar{P}, \tag{2}$$

where $\bar{P}$ denotes the regular charging power of one charging pile during one time slot.[1]

Let $\mathbb{I}$ denote the expected set of EVs that are charged in the parking lot during the entire period and $\bar{\mathbb{I}}(t)$ denote the set of EVs that are connected to the charging system during time slot t, respectively. Thus, $\bar{\mathbb{I}}(t) \subset \mathbb{I}$ and $\mathbb{I} = \bigcup_{t=1}^{T} \bar{\mathbb{I}}(t)$ always hold. Then, we have

$$\begin{cases} 0 \leq x_{i,t} \leq 1, & \text{if } i \in \bar{\mathbb{I}}(t); \\ x_{i,t} = 0, & \text{otherwise.} \end{cases} \tag{3}$$

Let $\bar{E}_t$ denote the total charging load of the parking lot from the connected EVs during time slot t. $\bar{E}_t$ can be given by

$$\bar{E}_t = \sum_{i \in \bar{\mathbb{I}}(t)} E_{i,t} = \sum_{i \in \bar{\mathbb{I}}(t)} x_{i,t}\bar{P}. \tag{4}$$

[1] According to $SAEJ1772 - 2009$ standard in [22], the charging power of the charging pile with the AC Level II charging mode is 19.2 kW. Thus, $\bar{P} = 19.2 * 24/T = 460.8/T(kWh)$.

Note that the total charging load $\bar{E}_t$ not only depends on the charging decision $x_{i,t}$ and the regular charging power $\bar{P}$, but also depends on the set of the connected EVs $\bar{\mathbb{I}}(t)$. Let $\bar{E}_t^{\max}$ denote the maximal value of $\bar{E}_t$. Without considering the limited energy supply, $\bar{E}_t^{\max}$ can be given by

$$\bar{E}_t^{\max} = \sum_{i \in \bar{\mathbb{I}}(t)} \hat{x}_{i,t} \bar{P}, \quad \forall t, \tag{5}$$

where $\hat{x}_{i,t} = 1$ iff EV i belongs to $\bar{\mathbb{I}}(t)$. Obviously, the maximal charging load $\bar{E}_t^{\max}$ depends on $\bar{\mathbb{I}}(t)$.

B. CHARGING REQUIREMENT MODEL OF EVs

Generally, different EVs may have different arrival times, departure times, and charging requirements, which impact the charging decision. According to the status of EVs, we classify them into two classes: The connected EVs and the upcoming EVs.[2] For each connected EV, it needs to report its arrival time, departure time and charging requirement to the central controller when it is connected to the parking lot. For the upcoming EVs, the central controller needs to estimate their information and then update them based on the realtime information since it is difficult to know their information with a high accuracy in advance.

For connected EV i, let A_i, D_i and R_i^O denote its arrival time, departure time and charging requirement, respectively. Obviously, EV i only can be charged during time slot t, $t \in [A_i, D_i]$, and the relationship between EV i and $\bar{\mathbb{I}}(t)$ can be defined as

$$\begin{cases} i \in \bar{\mathbb{I}}(t), & \text{if } t \in [A_i, D_i]; \\ i \notin \bar{\mathbb{I}}(t), & \text{otherwise.} \end{cases} \tag{6}$$

Let M_t^A and M_t^L denote the number of EVs that arrive at the parking lot and that leave the parking lot during time slot t, respectively. We have

$$\sum_{t=1}^{\bar{t}} (M_t^A - M_t^L) = \sum_{i \in \bar{\mathbb{I}}(\bar{t})} \hat{x}_{i,\bar{t}}, \quad \forall \bar{t}. \tag{7}$$

For the upcoming EVs, based on the statistics of the workplace parking lots [23], the distribution of their arrival times can be approximated to a normal distribution, where the mean and standard deviation are μ_A and σ_A, while their departure times can be approximated to another normal distribution, where the mean and standard deviation are μ_L and σ_L, respectively. Let λ denote the expected total number of the EVs that are charged in the parking lot during the entire period. We have

$$M_{t'}^A = \lambda \int_{t'}^{t'+1} f_A(x) d_x = \lambda (F_A(t'+1) - F_A(t')), \tag{8}$$

where $f_A(t)$ is the probability density function (PDF) of the arrival times, and $F_A(t')$ is the corresponding cumulative distribution function (CDF). In addition, a lognormal distribution function, with two parameters μ_D and σ_D, can approximate the PDF of EVs' travel distances [23], given by

$$f_{\hat{D}}(x : \mu_D, \sigma_D) = \frac{1}{x \sigma_D \sqrt{2\pi}} \exp\{-\frac{(\ln x - \mu_D)^2}{2\sigma_D^2}\}. \tag{9}$$

Let E_D denote EV's expected energy consumption per kilometer. The expected charging requirement of each upcoming EV can be given by $E_D \exp\{\mu_D + \frac{\sigma_D^2}{2}\}$.

Let R_i^t denote the charging requirement of EV i at time slot t. According to the EV charging requirement and the previous charging decision $\{x_{i,t}, \forall i \in \mathbb{I}\}$, the charging requirement $R_i^{\bar{t}}$ at current time slot $\bar{t}$ can be given by

$$R_i^{\bar{t}} = \begin{cases} R_i^O - \sum_{t=A_i}^{\bar{t}-1} x_{i,t} \bar{P}, & \text{if } A_i < \bar{t}; \\ R_i^O, & \text{if } A_i = \bar{t}; \\ E_D \exp\{\mu_D + \frac{\sigma_D^2}{2}\}, & \text{if } A_i > \bar{t}. \end{cases} \tag{10}$$

Note that the expected charging requirements of the connected EVs will be changed by the charging decision while the charging requirements of upcoming EVs will be updated when the EVs connect to the parking lot.

C. ENERGY SUPPLY MODEL OF THE PARKING LOT

The parking lot can be powered by both the PV system and the power grid. Let E_t^R denote the solar energy that is collected by the PV system, E_t^{R0} denote the total amount of excessive harvested solar energy that cannot be scheduled to any EV by the parking lot, and E_t^G denote the total amount of energy from the power grid during time slot t, respectively. According to the energy conservation constraint, we have

$$\bar{E}_t = E_t^G + E_t^R - E_t^{R0}, \tag{11}$$

where

$$E_t^{R0} \le E_t^R, \quad \forall t. \tag{12}$$

Generally, for safety and reliability concerns, the power grid always issues an upper bound on its available energy for the parking lot during one time slot, denoted by $\bar{E}^G$. Thus, for the total energy from the power grid, we have

$$E_t^G \le \bar{E}^G, \quad \forall t. \tag{13}$$

In addition, due to the limited charging load of the connected EVs, the total energy from the power grid satisfies

$$E_t^G = \min\{\bar{E}_t - E_t^R + E_t^{R0}, \bar{E}^G\}. \tag{14}$$

Note that the total amount of energy from the power grid depends on not only the charging load of the connected EVs, but also the total amount and the utilization of the solar energy during the time slot. The expected total charging load $\bar{E}_t$ of the parking lot during time slot t satisfies

$$\bar{E}_t \le E_t^R + \bar{E}^G, \quad \forall t. \tag{15}$$

Since it is difficult to know the precise value of the solar energy collected by the PV system in the future, the central

[2]The connected EVs denotes the EVs that have arrived at the parking lot and connected to the charging pile at current time slot $\bar{t}$, and the upcoming EVs denotes the EVs that are expected to connect to the charging pile in future.

controller needs to estimate the solar energy in the upcoming time slots. Let $E_{t'}^R$ and $\hat{E}_{t'}^R$ respectively denote the estimation and the real value of the solar energy during time slot t', and ε denote maximal estimation error in percentage. Thus, we have

$$E_{t'}^R \in [(1-\varepsilon)\hat{E}_{t'}^R, (1+\varepsilon)\hat{E}_{t'}^R], \tag{16}$$

where $t' \in (\bar{t}, \bar{t}+T]$. Fortunately, several existing solar energy prediction models, e.g., the historical-data-based method [24] and statistical-learning based method [25], show that the short-term estimation of the solar energy can be guaranteed within a limited error range. Hence, we set $\varepsilon \leq 20\%$ in this paper. By now, the controller can manage the EV charging processes based on the estimation of the solar energy and then update its decision when the realtime information is obtained.

D. OPERATION REQUIREMENT OF THE PARKING LOT

For the parking lot, the charging decision, $\{x_{i,t}, \forall i, t\}$, needs satisfy the charging requirements of all the EVs. Thus, for each EV i, we have

$$R_i^O = \sum_{t=1}^{T} x_{i,t}\bar{P} = \sum_{t=A_i}^{D_i} E_{i,t},$$

since $x_{i,t} = 0$ when $t \notin [A_i, D_i]$. It means that EV i's charging requirement should be satisfied when it is connected to the parking lot.

For connected EV i, since the charging requirement $R_i^{\bar{t}}$ has been changed according to (10), the charging decision, $\{x_{i,t}, \forall t \in [\bar{t}, T]\}$, should satisfy

$$R_i^{\bar{t}} = \sum_{t=\bar{t}}^{T} x_{i,t}\bar{P} = \sum_{t=\bar{t}}^{D_i} E_{i,t} \tag{17}$$

For upcoming EV i, the charging decision, $\{x_{i,t}, \forall t \in [\bar{t}, T]\}$, should satisfy

$$R_i^{\bar{t}} = \sum_{t=\bar{t}}^{T} x_{i,t}\bar{P} = \sum_{t'=A_i}^{D_i} E_{i,t}, \tag{18}$$

where $A_i > \bar{t}$ and $D_i = \mu_L$.

E. OPERATION GOALS OF THE PARKING LOT

In general, the main concern of the parking lot is to maximize its benefit while satisfying the charging requirements of all the EVs. Here, the benefit of the parking lot depends on the energy cost and the income. Since the collecting cost of the solar energy is low once the PV system has been installed, only the electricity cost from the power grid is considered.

To smoothen the charging load on the power grid, the electricity spot price, consisting a load-independent part and a load dependent part, has been widely employed [26]–[28]. Specifically, the electricity cost of the parking lot, denoted by C_t^G, is

$$C_t^G = a_1(E_t^G)^2 + a_2E_t^G, \tag{19}$$

where $a_1E_t^G$ and a_2 are load-dependent and load-independent prices respectively.

Let a_3 denote the income of the parking lot for charging one kWh energy to EVs. Since the total energy charged to EVs during time slot t is $\bar{E}_t$, the total income of the parking lot during time slot t is $a_3\bar{E}_t$.

The benefit of the parking lot during time slot t is $a_3\bar{E}_t - (a_1(E_t^G)^2 + a_2E_t^G)$. Let $C_T^{\bar{t}}$ denote the expected total benefit of the parking lot from the current time slot $\bar{t}$ to the end of the time period T, which can be given by

$$C_T^{\bar{t}} = \sum_{t=\bar{t}}^{T}\Big(a_3\bar{E}_t - (a_1(E_t^G)^2 + a_2E_t^G)\Big). \tag{20}$$

F. PROBLEM FORMULATION

In this paper, we aim at designing an optimal charging scheduling scheme to maximize the total benefit of the parking lot while satisfying the charging requirements of all the connected EVs. Let $\boldsymbol{X}^{\bar{t}} = \{x_{i,\bar{t}}, x_{i,\bar{t}+1}, \cdots, x_{i,T}, \forall i\}$ be the charging decisions from current time slot $\bar{t}$ to the end of the time period T. The charging scheduling optimization problem for the parking lot can be formulated as follows:

$$\mathbf{P0}: \max_{\boldsymbol{X}^{\bar{t}}} \; C_T^{\bar{t}} \tag{21}$$

$$\text{s.t. } \bar{E}_t \leq E_t^R + \bar{E}^G, \quad \forall t \in [\bar{t}, T], \tag{22}$$

$$0 \leq x_{i,t} \leq 1, \quad \forall i \in \mathbb{I}(t),\; t \in [\bar{t}, T], \tag{23}$$

$$\bar{R}_i^{\bar{t}} = \sum_{t=\bar{t}}^{T} E_{i,t}, \quad \forall i. \tag{24}$$

The objective function is to maximize the total benefit of the parking lot from current time slot $\bar{t}$ to the end of the time period T. The first constraint gives the upper bound on the charging load, and the second constraint gives the available range of the charging decision. The third constraint ensures that the charging requirements of all the EVs should be satisfied.

If the amount of the solar energy and the charging requirements of all the EVs are known, the charging scheduling optimization problem is a convex optimization problem, which can be solved by existing centralized toolboxes. However, due to the time-space coupling variables and the high computation complexity, these toolboxes may not satisfy the realtime operation requirement. Furthermore, these approaches cannot deal with the realtime dynamics of EV charging requirements and the solar energy from PV system. In order to solve this problem in an efficient way, we analyze the relationship among the system parameters, and derive several necessary conditions for optimal solution to simplify the primal problem, and then propose a distributed algorithm to update the charging decision in realtime.

IV. SYSTEM PARAMETER ANALYSIS

Let $R_{\mathbb{I}}^{\bar{t}}$ denote the total amount of the EV charging requirements during the remainder time period at current time slot $\bar{t}$. For $R_{\mathbb{I}}^{\bar{t}}$, we have the following Lemma:

Lemma 1: The expected value of $R_{\mathbb{I}}^{\bar{t}}$ can be given by

$$R_{\mathbb{I}}^{\bar{t}} = \sum_{i\in\bar{\mathbb{I}}(\bar{t})} R_i^{\bar{t}} + \sum_{t=\bar{t}+1}^{T} M_t^A E_D \exp\{\mu_D + \frac{\sigma_D^2}{2}\}. \quad (25)$$

Proof: In general, the total amount of the expected EV charging requirements $R_{\mathbb{I}}^{\bar{t}}$ can be divided into two parts: the first part depends on charging requirements of the connected EVs and the other part depends on that of upcoming EVs.

Since each connected EV i needs to report its charging requirement R_i^O to the parking lot, its current charging requirement $R_i^{\bar{t}}$ can be obtained by (10). Thus, the total amount of the charging requirements of the connected EVs at current time slot $\bar{t}$ can be obtained by $\sum_{i\in\bar{\mathbb{I}}(\bar{t})} R_i^{\bar{t}}$.

Based on the distribution of EVs' arrival times, M_t^A EVs are expected to arrive at the parking lot during time slot t and the expected charging requirement of each upcoming EV is $E_D \exp\{\mu_D + \frac{\sigma_D^2}{2}\}$. Thus, the total amount of the expected charging requirements of upcoming EVs is $\sum_{t=\bar{t}+1}^{T} M_t^A E_D \exp\{\mu_D + \frac{\sigma_D^2}{2}\}$.

Thus, the total amount of the expected EV charging requirements $R_{\mathbb{I}}^{\bar{t}}$ can be given by (25). ■

Note that $R_{\mathbb{I}}^{\bar{t}} = \lambda E_D \exp\{\mu_D + \frac{\sigma_D^2}{2}\}$ when $\bar{t} = 0$.

In order to satisfy the charging requirements of all the EVs, the total amount of the energy from the power grid $\sum_{t=\bar{t}}^{T} E_t^G$ should satisfy the following Lemma:

Lemma 2: If $\bar{E}^G$ is large enough, the total amount of the energy from the power grid $\sum_{t=\bar{t}}^{T} E_t^G$ and the total amount of the charging requirements $R_{\mathbb{I}}^{\bar{t}}$ should satisfy

$$\sum_{t=\bar{t}}^{T} E_t^G = R_{\mathbb{I}}^{\bar{t}} - \sum_{t=\bar{t}}^{T} (E_t^R - E_t^{R0}). \quad (26)$$

Proof: In order to satisfy the charging requirements of all the EVs, (17) and (18) should be satisfied simultaneously. Since the total charging load of all the connected EV during time slot t is $\sum_{i\in\bar{\mathbb{I}}(t)} E_{i,t}$, the following constraint should be satisfied

$$R_{\mathbb{I}}^{\bar{t}} = \sum_{i\in\bigcup_{t=\bar{t}}^{T}\bar{\mathbb{I}}(t)} R_i^{\bar{t}} = \sum_{t=\bar{t}}^{T}\sum_{i\in\bar{\mathbb{I}}(t)} E_{i,t} = \sum_{t=\bar{t}}^{T} \bar{E}_t.$$

According to E_t^G given by (11), i.e., $\bar{E}_t = E_t^G + E_t^R - E_t^{R0}$, if $\bar{E}^G$ is large enough, we have

$$R_{\mathbb{I}}^{\bar{t}} = \sum_{t=\bar{t}}^{T} \Big(E_t^G + (E_t^R - E_t^{R0})\Big)$$
$$\Longrightarrow \sum_{t=\bar{t}}^{T} E_t^G = R_{\mathbb{I}}^{\bar{t}} - \sum_{t=\bar{t}}^{T} (E_t^R - E_t^{R0}). \quad (27)$$

■

Given the charging requirements of all the EVs $R_{\mathbb{I}}^{\bar{t}}$ and the solar energy E_t^R, it can be found that the total amount of energy from the power grid, $\sum_{t=\bar{t}}^{T} E_t^G$, is an increasing function of the unused solar energy E_t^{R0}.

By analyzing the relationships among $C_T^{\bar{t}}$, E_t^G and E_t^{R0}, we have the following Lemma:

Lemma 3: The expected total benefit of the parking lot $C_T^{\bar{t}}$ is a decreasing function of E_t^G and E_t^{R0}.

Proof: Since the charging requirements of all the EVs should be satisfied, we have

$$\sum_{i\in\mathbb{I}} R_i^{\bar{t}} = \sum_{t=\bar{t}}^{T} \bar{E}_t. \quad (28)$$

According to energy conservation constraint (11), we have

$$\sum_{t=\bar{t}}^{T} E_t^G = \sum_{t=\bar{t}}^{T} \Big(\bar{E}_t - (E_t^R - E_t^{R0})\Big). \quad (29)$$

Based on (28) and (29), the total benefit $C_T^{\bar{t}}$ can be written as

$$C_T^{\bar{t}} = (a_3 - a_2)\sum_{i\in\mathbb{I}} R_i^{\bar{t}} - \sum_{t=\bar{t}}^{T} \Big(a_1 (E_t^G)^2 - a_2 (E_t^R - E_t^{R0})\Big). \quad (30)$$

It can be found that the total cost $C_T^{\bar{t}}$ is a decreasing function of E_t^G and a decreasing function of E_t^{R0}. ■

For E_t^G and E_t^{R0}, we have the following theorem:

Theorem 1: For the optimal charging decision, at least one of E_t^G and E_t^{R0} should equal 0.

Proof: According to (14) and (27), both of E_t^G and $\sum_{t=\bar{t}}^{T} E_t^G$ are increasing functions of E_t^{R0}. According to the definition of $C_T^{\bar{t}}$ given by (30), its expected value is an increasing function of the unused solar energy E_t^{R0} and the energy from the power grid E_t^G. To minimize $C_T^{\bar{t}}$, E_t^{R0} should be minimized. The following conclusion can be obtained: if $\bar{E}_t \leq E_t^R$, $E_t^{R0} \geq 0$ and $E_t^G = 0$; Otherwise, $E_t^{R0} = 0$ and $E_t^G > 0$. Thus, at least one of E_t^G and E_t^{R0} should equal 0. ■

The maximal charging load $\bar{E}_t^{\max}$ is bounded by both the amount of energy from the PV system and the power grid, and the number of connected EVs during time slot t. Thus, for the maximal charging load $\bar{E}_t^{\max}$, we have the following lemma:

Lemma 4: The maximal charging load $\bar{E}_t^{\max}$ during time slot t can be given by

$$\bar{E}_t^{\max} = \min\{\sum_{\hat{t}=1}^{t} (M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P}, E_t^R + \bar{E}^G\} \quad \forall t. \quad (31)$$

Proof: According to the definition of charging decision $x_{i,t}$, $0 \leq x_{i,t} \leq 1$ should be satisfied for any connected EV i during time slot t. Since the regular charging load of each connected EV is $\bar{P}$, the maximal charging load $\bar{E}_t^{\max}$ from all the connected EVs is

$$\bar{E}_t^{\max} = \sum_{\hat{t}=1}^{t} (M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P}, \quad (32)$$

according to (5) and (7). In addition, since the charging load during time slot t should satisfy constraint (15), i.e., $\bar{E}_t \leq E_t^R + \bar{E}^G$, another bound on the charging load of all the connected EVs is

$$\bar{E}_t^{\max} = E_t^R + \bar{E}^G. \tag{33}$$

Thus, the maximal charging load $\bar{E}_t^{\max}$ from all the connected EVs can be given by (31). ■

Based on Lemma 4 and Theorem 1, we have the following lemma for the energy from the power grid E_t^G:

Lemma 5: The energy from the power grid E_t^G satisfies

$$E_t^G \leq \min\{\sum_{\hat{t}=1}^{t}(M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P} - E_t^R + E_t^{R0}, \bar{E}^G\}. \tag{34}$$

Proof: According to Lemma 4, the charging load $\bar{E}_t$ is bounded by (31). Thus, based on the number of the connected EVs and Theorem 1, the energy from the power grid E_t^G can be divided into three cases:

Case I: When $E_t^R \geq \sum_{\hat{t}=1}^{t}(M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P}$, we have

$$\bar{E}_t = E_t^R - E_t^{R0} \Longrightarrow E_t^G = 0.$$

Case II: When $E_t^R < \sum_{\hat{t}=1}^{t}(M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P} \leq E_t^R + \bar{E}^G$, we have

$$\bar{E}_t \leq \sum_{\hat{t}=1}^{t}(M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P} \Longrightarrow E_t^G \leq \sum_{\hat{t}=1}^{t}(M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P} - E_t^R.$$

Case III: When $\sum_{\hat{t}=1}^{t}(M_{\hat{t}}^A - M_{\hat{t}}^L)\bar{P} > E_t^R + \bar{E}^G$, we have

$$\bar{E}_t \leq E_t^R + \bar{E}^G \Longrightarrow E_t^G \leq \bar{E}^G.$$

Thus, the maximal amount of energy that from the power grid during time slot t can be given by the right hand of (34). ■

Based on the above analysis, we obtain the relationship among the total benefit $C_T^{\bar{t}}$, the energy from the power grid E_t^G, and the unused solar energy E_t^{R0}, which can be used to simplify Problem **P0** in the following section.

V. PROBLEM TRANSFORMATION AND DCSS

In this section, we first transform Problem **P0** into an easier to solve one. Then, we propose a DCSS to obtain the optimal charging decision in realtime.

According to Lemma 1, the total amount of the EV expected charging requirements $R_{\mathbb{I}}^{\bar{t}}$ at current time slot $\bar{t}$ is a constant. In addition, the amount of the solar energy during time slot $\bar{t}$ and upcoming time slot t' are given. Thus, the total benefit of the parking lot, defined by (30), can be rewritten as

$$C_T^{\bar{t}} = \xi - \sum_{t=\bar{t}}^{T}\left(a_1(E_t^G)^2 + a_2 E_t^{R0}\right), \tag{35}$$

where $\xi = (a_3 - a_2)R_{\mathbb{I}}^{\bar{t}} + a_2\sum_{t=\bar{t}}^{T} E_t^R$, which can be treated as a variable-independent constant in this paper.

Remark: In order to maximize the total benefit, $\sum_{t=\bar{t}}^{T}\left(a_1(E_t^G)^2 - a_2 E_t^{R0}\right)$ should be minimized. According to Lemma 5 and Theorem 1, the optimal values of E_t^{R0} and E_t^G satisfy the following constraints: 1) $E_t^{R0} > 0$ and $E_t^G = 0$ hold iff $E_t^R > \bar{E}_t$; 2) $E_t^{R0} = 0$ and $E_t^G = 0$ hold iff $E_t^R = \bar{E}_t$; 3) $E_t^{R0} = 0$ and $E_t^G = \min\{\bar{E}_t - E_t^R, \bar{E}_t^G\}$ iff $\bar{E}_t > E_t^R$. For conditions 1) and 2), the energy that is charged to the connected EVs cannot be increased since it reaches its upper bound and $E_t^G = 0$, and the optimal solution is to set $x_{i,t}$ as large as possible. For condition 3), $E_t^{R0} = 0$ holds, and we only needs to minimize $\sum_{t=\bar{t}}^{T} a_1(E_t^G)^2$.

By now, Problem **P0** can be transformed as:

$$\mathbf{P1}: \min_{X^{\bar{t}}} \sum_{t=\bar{t}}^{T} a_1(E_t^G)^2 \tag{36}$$

$$\text{s.t. } \bar{E}_t \leq E_t^R + \bar{E}^G, \quad \forall t \in [\bar{t}, T], \tag{37}$$

$$0 \leq x_{i,t} \leq 1, \quad \forall i \in \bar{\mathbb{I}}(t),\ t \in [\bar{t}, T], \tag{38}$$

$$\bar{R}_i^{\bar{t}} = \sum_{t=\bar{t}}^{T} E_{i,t}, \quad \forall i. \tag{39}$$

It can be found that the objective function in problem **P1** is an increasing and convex function of charging decision $\boldsymbol{X}^{\bar{t}}$ since E_t^G is a linear function of charging decision $\boldsymbol{X}^{\bar{t}}$. Thus, the transformed problem is a convex optimization problem at $\bar{t}$, which can be solved by the dual decomposition method and subgradient method.

Let $\boldsymbol{\beta} = \{\beta_{\bar{t}}, \beta_{\bar{t}+1}, \cdots, \beta_T\}$ and $\boldsymbol{\gamma} = \{\gamma_i, \forall i \in \mathbb{I}\}$ be the Lagrange multipliers. The partial Lagrangian of Problem **P0** at current time slot $\bar{t}$ is

$$L(\boldsymbol{X}^{\bar{t}}, \boldsymbol{\beta}, \boldsymbol{\gamma}) = \sum_{t=\bar{t}}^{T} a_1(E_t^G)^2 + \sum_{t=\bar{t}}^{T}\beta_t(\sum_{i\in\bar{\mathbb{I}}(t)} E_{i,t} - E_t^R - \bar{E}^G) + \sum_{i\in\mathbb{I}}\gamma_i(\sum_{t=\bar{t}}^{T} E_{i,t} - \bar{R}_i^{\bar{t}}). \tag{40}$$

The dual problem of Problem **P1** is

$$D(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \sup_{0\leq x_{i,t}\leq 1, \quad \forall i\in\bar{\mathbb{I}}(t)} L(\boldsymbol{X}^{\bar{t}}, \boldsymbol{\beta}, \boldsymbol{\gamma}). \tag{41}$$

The objective of the dual problem is

$$\min_{\boldsymbol{\beta},\boldsymbol{\gamma}} D(\boldsymbol{\beta}, \boldsymbol{\gamma}). \tag{42}$$

Given $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, the Lagrangian of Problem **P1** is an increasing and convex function of $x_{i,t}$. Thus, the problem can be solved by the subgradient method, i.e.,

$$x_{i,t}^{k+1} = [x_{i,t}^k - \alpha\frac{\partial L(\boldsymbol{X}^{\bar{t}}, \boldsymbol{\beta}, \boldsymbol{\gamma})}{\partial x_{i,t}}]_0^1; \tag{43}$$

where α is the step size and k is the iteration number. The dual problem can be solved using the subgradient projection method, where the Lagrangian multipliers, β_t, and γ_i, are adjusted in the direction opposite to the subgradients, i.e.,

$$\beta_t^{k+1} = [\beta_t^k + \alpha\frac{\partial D(\boldsymbol{\beta}, \boldsymbol{\gamma})}{\partial \beta_t}]^+, \tag{44}$$

$$\gamma_i^{k+1} = \gamma_i^k + \alpha\frac{\partial D(\boldsymbol{\beta}, \boldsymbol{\gamma})}{\partial \gamma_i}, \tag{45}$$

where $[\bullet]^+$ denotes $\max\{0, \bullet\}$. The optimal charging decision based on the information at the current time slot will be obtained by the proposed algorithm if a small enough step-size is selected [29].

Due to uncertainty and fluctuation of solar energy and the time-varying EV charging requirements in future, the charging decision made at current time slot $\bar{t}$ may not be the optimal charging decision for future time slots. Thus, the central controller needs to update the charging decision according to the realtime information. In this paper, MPC is adopted to deal with dynamic system parameters since it optimizes the decision in the current time slot, while tracking the the performance in future time slots.

Specifically, at current time slot $\bar{t}$, based on the charging decision $\boldsymbol{X}^{\bar{t}-1}$ and the realtime information from the EVs that just arrived at the parking lot, the central controller updates the charging requirements of connected EVs $\{R_i^{\bar{t}}, \forall i \in \mathbb{I}\}$. Also, the central controller collects the information of the solar energy $\hat{E}_{\bar{t}}^R$. Then, it calculates the optimal charging decision $\boldsymbol{X}^{\bar{t}}$, and implements the charging decision $\{x_{i,\bar{t}}^{\bar{t}}, \forall i \in \bar{\mathbb{I}}(\bar{t})\}$. At time slot $\bar{t}+1$, the central controller updates $\{R_i^{\bar{t}+1}, \forall i \in \mathbb{I}\}$ and $\hat{E}_{\bar{t}+1}^R$ based on the realtime and estimated information again, and then calculates the optimal charging decision and implements the charging decision for time slot $\bar{t}+1$. The program will be executed continuously until $\bar{\mathbb{I}}(\bar{t}) = \emptyset$ or $\bar{t} = T$. This DCSS is sketched as Algorithm 1.

Algorithm 1 The DCSS

Initialization $\bar{P}$,λ, μ_A, σ_A, μ_L, σ_L, μ_D, σ_D, E_D, $\hat{E}_t^R$,T,$\bar{E}^G$

- **for** $\bar{t} = 1, 2, \cdots, T$

  1) EV i, which arrives at the parking lot during time slot $\bar{t}$, reports $\{A_i,\ D_i,\ R_i^O\}$ to the central controller;

  2) The central controller updates $\hat{E}_{\bar{t}}^R$ and $\{R_i^{\bar{t}}, i \in \mathbb{I}\}$ based on the realtime information;

  3) The central controller updates the charging decision by solving Problem **P1** distributively;

  4) The central controller implements the charging decision $\{x_{i,\bar{t}}^{\bar{t}}, \forall i \in \bar{\mathbb{I}}(\bar{t})\}$ by toggling the corresponding switches;

  end for

return $\{x_{i,t}^t, \forall i, t\}$, $\{\hat{E}_t^R, \forall t\}$, and $\{E_t^G, \forall t\}$.

Noted that, the time-horizon will be narrowed with the increase of time slot $\bar{t}$. The operation flow of the designed DCSS can be found in Fig. 2.

VI. NUMERICAL SIMULATIONS

To demonstrate the performance of the proposed DCSS, numerical simulations are conducted in comparison with the Two-stage scheduler proposed in [14], which calculates an upper bound of charging load based on the estimated information and then updates the charging decision based on the realtime information. We consider a workplace parking lot for

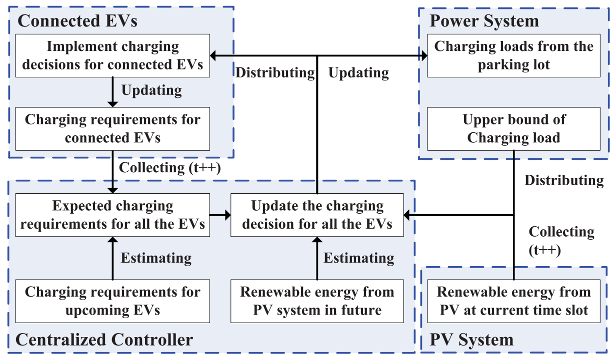
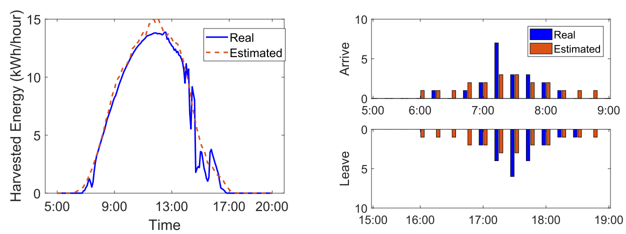


FIGURE 2. The operation flow of the designed DCSS ($t++$ denotes the next time slots).

a company, whose office hours are from 8:00am to 5:00pm. The parking lot is powered by both a 15kWh PV system and the power grid with an upper bound $\bar{E}^G = 40$kWh per hour. Let one day be a time period and one quarter-hour be a time slot, such that T=96. The maximal estimation error of harvested solar energy is $\epsilon = 0.2$. Similar as the setting from [23], the arrival times and leave times of EVs follow (μ_A = 7:30, σ_A = 3 slots) and (μ_L = 17:30, σ_L = 3 slots), respectively, and the total expected amount of EVs during entire time period is $\lambda = 20$. The travel distance of EVs follows a log-normal distribution with ($\mu_D = 3.37$, $\sigma_D = 0.5$ mile) and the expected energy consumption is 0.2kWh/mile. The electricity spot price is $a_1 = \$0.15/kWh$ and $a_2 = \$0.015/kWh^2$ and the income of providing charging service is $a_3 = \$0.3/kWh$, respectively.

A. CASE STUDY

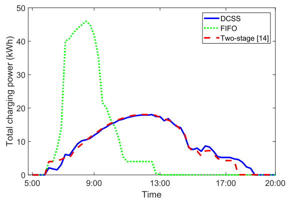
For fair comparison, we set the total number of EVs and their total charging requirements according to the expected values. However, different EVs may have different charging requirements. The estimated and actual data of the solar energy is shown in 3(a) and the arrival and departure times of EVs are shown in Fig. 3(b).



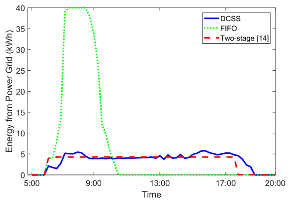
(a) (b)

FIGURE 3. Simulation setting: a) Solar energy; b) Arrive and departure times.

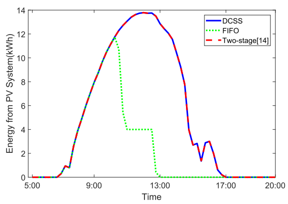
The total charging load of connected EVs, load on the power grid, and utilization of the solar energy are shown in Fig. 4, respectively. It can be found that both the proposed DCSS and Two-stage scheduler in [14] can reduce the peak load on the power grid significantly comparing to the FIFO scheduler. Furthermore, both of the proposed DCSS and the



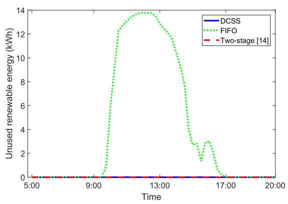
(a) $\bar{E}_t$



(b) E_t^G



(c) $E_t^R - E_t^{R0}$



(d) E_t^{R0}

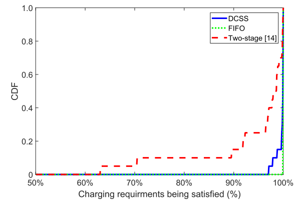
FIGURE 4. Simulation results: a) The total charging power of the parking lot; b) The total energy from the Power Grid; c) The total energy from the PV system; d) The total amount of unused solar energy.

Two-stage schedulers can utilize the solar energy in an efficient way, while the parking lot with FIFO scheduler wasted a lot of the solar energy since all the connected EVs have been charged too soon to fully utilize the solar energy source. From Fig. 4(a), our algorithm has small fluctuations since the actual collected solar energy is different from the expected one and our algorithm adjust the scheduling scheme based on the realtime information.

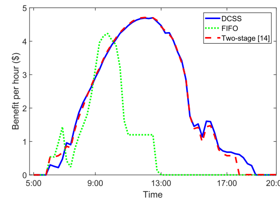
Fig. 5 shows the Cumulative Distribution Function (CDF) of the charged energy to the charging requirement for the connected EVs and the benefit of the parking lot during each time slot, respectively. Since the parking lot with FIFO scheduler will charge the connected EVs to full as soon as possible, the charging requirements of all the connected EVs can be satisfied. The proposed DCSS can charge more than 85% connected EVs to full and all the connected EVs to more than 95% their charging requirements, while the Two-stage scheduler in [14] only charges 30% connected EVs to full and near 25% connected EVs under 95% their charging requirements. That is because the upper bound on the charging load on the power grid in existing work depends on the estimation of the charging requirements and the solar energy, and thus cannot guarantee the performance when the charging requirements is time-varying. From Fig. 5(b), it can be found that the proposed DCSS obtains the highest benefit, about 200% higher than that of FIFO scheduler. Furthermore, although the parking lot under the proposed DCSS buys more energy from the power grid, it can obtain a higher benefit than the Two-stage scheduler in [14].

B. SYSTEM STATISTICAL PERFORMANCE

To explore the performance of the proposed algorithm, we assumed that the number of arrived EVs varies in [16, 26] and applied 100 more sets of the operational data for each of them. The expected value of the peak load on the



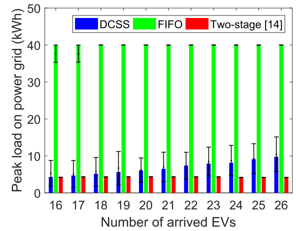
(a) CDF of $\sum_t E_{i,t}/R_i^O$



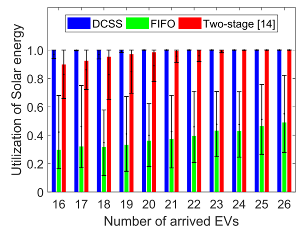
(b) $C_t^{\bar{t}}$

FIGURE 5. The performance: a) the CDF of the charged energy to the charging requirement; b) The total benefit of the parking lot.

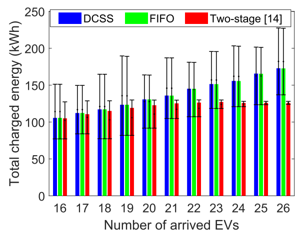
power grid, the utilization of the solar energy, total amount of charged energy, and the total benefit can be found at Fig. 6, respectively.



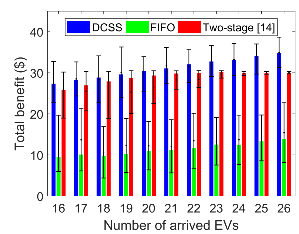
(a) $\max\{E_t^G\}$



(b) $1 - \sum E_t^{R0} / \sum \hat{E}_t^R$



(c) $\sum_t \bar{E}_t$



(d) $\sum C_t^{\bar{t}}$

FIGURE 6. The performance: a) The peak load on the power grid; b) the utilization of solar energy; c) The total amount of charged energy to the connected EVs; d) The total benefit of the parking lot.

Form Figs. 6(a)-6(c), it can be found that the Two-stage scheduler keeps the peak load on the power grid at the lowest level. However, with the gap between expected and real numbers of EVs increase, more EV charging requirements cannot be satisfied, e.g., when the number of EVs is 26, near 30% EV charging requirements cannot be satisfied. This is because the Two-stage scheduler cannot make a quick response to the time-varying information so it fails to satisfy the EV charging requirements with the increase of the number of EVs. The FIFO scheduler has the highest peak load on the power gird and lowest utilization of the solar energy. Note that, the proposed DCSS can adjust the load on the power Grid based on the realtime EV charging requirement and the solar energy, such that it can make use of all the solar energy and satisfy the EV charging requirements with a lower load on the power grid.

From results shown in Fig. 6(d), the proposed DCSS has the highest benefit of the parking lot comparing to other algorithms. That's because the FIFO scheduler has a high electricity cost due to its high peak load on the power grid while the Two-stage scheduler just satisfied part of the EV charging requirements due to its limited peak load on the power grid. Thus, the proposed DCSS can maximize the total benefit of the parking lot while satisfying the EV charging requirements and maximizing the utilization of the solar energy.

VII. CONCLUSION

In this paper, we addressed the charging scheduling problem for the workplace parking lot powered by both the PV System and the power grid. Considering the realtime information collected by the central controller and the predictive values for upcoming EVs and solar energy, we formulated a benefit maximization problem for the parking lot. Then, we analyzed the relationship among the system parameters of the optimal solution, and derived some necessary conditions, which can be used to simplify the formulated problem. At last, we proposed a realtime DCSS to update the charging decision according to the realtime information collected by the central controller, such that near optimal charging decisions can be obtained. Simulation results demonstrated the efficiency of the proposed charging scheduling scheme, which can increase the benefit of the parking lot significantly, while satisfying the charging requirements of all the connected EVs.

The proposed DCSS can be extended and improved in various aspects. First, the effects of EV owners preference on the proposed DCSS can be investigated, e.g., considering variable charging requirements, flexible departure times, and other Quality of Service requirements. Second, the energy supply model for the parking lot can be extended to mutli-energy sources with different costs, and their effects on the proposed DCSS can be analyzed. Another interesting extension is taking the energy storage system (with/without extra cost) into consideration, such that the total benefit of the parking lot can be further increased.

REFERENCES

[1] United Nations Framework Convention on Climate Change (UNFCCC). (2000). *How Human Activities Produce Greenhouse Gases*. [Online]. Available: http://unfccc.int/cop3/fccc/climate/fact22.htm

[2] P. Nunes, R. Figueiredo, and M. C. Brito, "The use of parking lots to solar-charge electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 66, pp. 679–693, Dec. 2016.

[3] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," *IEEE Commun. Surveys Tuts.*, vol. 14, no. 4, pp. 944–980, 4th Quart., 2012.

[4] Z. M. Fadlullah, D. M. Quan, N. Kato, and I. Stojmenovic, "GTES: An optimized game-theoretic demand-side management scheme for smart grid," *IEEE Syst. J.*, vol. 8, no. 2, pp. 588–597, Jun. 2014.

[5] R. Deng, Z. Yang, M. Chow, and J. Chen, "A survey on demand response in smart grids: Mathematical models and approaches," *IEEE Trans. Ind. Informat.*, vol. 11, no. 3, pp. 570–582, Jun. 2015.

[6] A. Mohamed, V. Salehi, T. Ma, and O. Mohammed, "Real-time energy management algorithm for plug-in hybrid electric vehicle charging parks involving sustainable energy," *IEEE Trans. Sustain. Energy*, vol. 5, no. 2, pp. 577–586, Apr. 2014.

[7] W. Tushar, C. Yuen, S. Huang, D. B. Smith, and H. V. Poor, "Cost minimization of charging stations with photovoltaics: An approach with EV classification," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 156–169, Jan. 2016.

[8] H. Liang, B. J. Choi, W. Zhuang, and X. Shen, "Optimizing the energy delivery via V2G systems based on stochastic inventory theory," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2230–2243, Dec. 2013.

[9] Z. Wei, Y. Li, Y. Zhang, and L. Cai, "Intelligent parking garage EV charging scheduling considering battery charging characteristic," *IEEE Trans. Ind. Electron.*, vol. 65, no. 3, pp. 2806–2816, Mar. 2018.

[10] R. Wang, G. Xiao, and P. Wang, "Hybrid centralized-decentralized (HCD) charging control of electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, p. 6728–6741, Aug. 2017.

[11] Y. Kim, J. Kwak, and S. Chong, "Dynamic pricing, scheduling, and energy management for profit maximization in PHEV charging stations," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1011–1026, Feb. 2017.

[12] C. Jin, X. Sheng, and P. Ghosh, "Optimized electric vehicle charging with intermittent renewable energy sources," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 6, pp. 1063–1072, Dec. 2014.

[13] L. Zhou, F. Li, C. Gu, Z. Hu, and S. Le Blond, "Cost/benefit assessment of a smart distribution system with intelligent electric vehicle charging," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 839–847, Mar. 2014.

[14] R. Wang, P. Wang, and G. Xiao, "Two-stage mechanism for massive electric vehicle charging involving renewable energy," *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 4159–4171, Jun. 2016.

[15] Y. Liu, R. Deng, and H. Liang, "Game-theoretic control of PHEV charging with power flow analysis," *AIMS ENERGY*, vol. 4, no. 2, pp. 379–396, 2016.

[16] 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.

[17] M. Wang, H. Liang, R. Zhang, R. Deng, and X. Shen, "Mobility-aware coordinated charging for electric vehicles in VANET-enhanced smart grid," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 7, pp. 1344–1360, Jul. 2014.

[18] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "Reliability studies of modern distribution systems integrated with renewable generation and parking lots," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 431–440, Jan. 2017.

[19] L. Liu, F. Kong, X. Liu, Y. Peng, and Q. Wang, "A review on electric vehicles interacting with renewable energy in smart grid," *Renew. Sustain. Energy Rev.*, vol. 51, pp. 648–661, Nov. 2015.

[20] 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.

[21] W. Lee, L. Xiang, R. Schober, and V. W. S. Wong, "Electric vehicle charging stations with renewable power generators: A game theoretical analysis," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 608–617, Mar. 2015.

[22] P. Ponticel. (Jan. 15, 2010). SAE Standard on EV Charging Connector Approved. SAE International. [Online]. Available: https://web.archive.org/web/20100121153150/http://www.sae.org:80/mags/aei/7479

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

[24] P. Bacher, H. Madsen, and H. A. Nielsen, "Online short-term solar power forecasting," *Solar Energy*, vol. 83, no. 10, pp. 1772–1783, 2009.

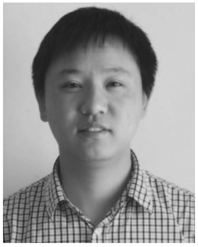
[25] B. Wolff, E. Lorenz, and O. Kramer, "Statistical learning for short-term photovoltaic power predictions," in *Computational Sustainability*. Cham, Switzerland: Springer, 2016, pp. 31–45.

[26] X. Liang, X. Li, R. Lu, X. Lin, and X. Shen, "UDP: Usage-based dynamic pricing with privacy preservation for smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 141–150, Mar. 2013.

[27] E. Veldman and R. A. Verzijlbergh, "Distribution grid impacts of smart electric vehicle charging from different perspectives," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 333–342, Jan. 2015.

[28] Z. Liu, Q. Wu, S. Huang, L. Wang, M. Shahidehpour, and Y. Xue, "Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 5173–5184, Sep. 2017.

[29] S. Boyd and L. N Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.



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