A Real-Time Charging Scheme for Demand Response in Electric Vehicle Parking Station

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***Abstract*—Demand response (DR) is a vital part in smart grid to restore the balance between electricity demand and supply. In this paper, a real-time charging scheme is proposed to coordinate the electric vehicle (EV) charging and accommodate DR programs in the parking station. The charging scheduling is formulated as a binary optimization problem because the on–off strategy is leveraged to achieve faster charging speed of EV. Given the computationally expensive nature of exhaustive search in solving the optimal solution of binary optimization problem, a convex relaxation method is developed as an alternative to compute the near-optimal charging schedules. Extensive simulation results show that the proposed work is able to satisfy EV charging demand while accommodating both types of DR programs in the parking station. The proposed work is also able to simultaneously maximize the number of EVs for charging and minimize the monetary expenses.**

***Index Terms*—Linear programming, convex relaxation, demand response, electric vehicle, smart grid.**

NOMENCLATURE

Indices and Sets

j, k	Index of scheduling time step.
N	Index of charging pole/connected EV.
C	Set containing all indices of charging poles.
Ψ^j	Set containing all weighting terms of charging poles.
Γ^j	Set containing all sorted indices of charging poles.

Operators

$Perm(\cdot)$	Operator for sorting the indices of charging poles.
$\Lambda_1(\cdot,\cdot)$	Operator for the first stage of rounding scheme.
$\Lambda_2(\cdot,\cdot)$	Operator for the second stage of rounding scheme.

Parameters and Variables

N	Total charging poles.
T_s	Sampling interval.
H	Total time periods for charging.
J	Total time steps for charging.
t_n^{arr}	Real-value arrival time of connected EV.
κ_n^{arr}	Arrival time step of connected EV.
t_n^{dep}	Real-value departure of connected EV.
κ_n^{dep}	Departure time step of connected EV.
δ_n^j	Connection status of charging pole.
γ_n^j	Current state-of-charge (SOC) of connected EV.
E_n^{cap}	Battery capacity of connected EV.
$\gamma^{\max}$	Upper SOC limit of EV.
$\gamma^{\min}$	Lower SOC limit of EV.
η	Charging efficiency
D_n^j	Remaining charging time steps of connected EV.
ψ_n	Membership ranking of connected EV.
$P_n^{\max}$	Maximum charging power of EV.
w_n^j	Charging priority weight of connected EV.
α^j	Electricity price.
$\alpha_{\max}$	Maximum electricity price.
$\alpha_{\min}$	Minimum electricity price.
ρ_n^j	Preference of charging pole to electricity price.
P_{total}	Installation capacity in parking station
P_{DR}^j	Load curtailment requested by DR program.
s_n^j	Binary charging decision of charging pole.
$\hat{s}_n^j$	Relaxed charging decision of charging pole.
q_n^k	Number of time steps needed to fully charge the EV.
h^j	Largest number of non-zero elements selected.
μ_{arv}	Mean arrival time of regular EVs.
σ_{arv}	Standard deviation of arrival time for regular EVs.
μ_{dep}	Mean departure time of regular EVs.
σ_{dep}	Standard deviation of departure time for regular EVs.
M	Total number of EVs.
γ_{avg}^f	Average final SOC of EVs.
τ_{avg}^f	Average charging time steps to attain the final SOC.

Matrices and Vectors

$\hat{\mathbf{s}}_n^k$	Vector containing the relaxed charging decisions of each charging pole for the remaining time steps.
$\hat{\mathbb{S}}^k$	Matrix containing the relaxed charging decisions of all charging poles for the remaining time steps.

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$\tilde{\mathbf{s}}_n^k$ Vector containing the binary charging decisions of each charging pole for the remaining time steps.

$\tilde{\mathbb{S}}^k$ Matrix containing the binary charging decisions of all charging poles for the remaining time steps.

$\tilde{\boldsymbol{\omega}}^j$ Vector containing the binary charging decisions of all charging poles at the current time step.

$\tilde{\mathbf{s}}_{top}$ Vector containing the non-zero elements.

I. Introduction

ELECTRIC vehicle (EV) is deemed as one alternative of internal combustion vehicle because it promises for better energy conversion efficiency and the reduction of greenhouse gases emission. Despite the benefits offered, EV can be considered as a high power appliance because it draws a significant amount of power from the charging pole during the charging process. The large-scale uncoordinated EV charging load is anticipated to introduce the new electric demands, which could lead to the energy shortage issue, and threaten the reliability and stability of power system [1]. Proper management of these large amount of EV charging loads without fatally harming the power grids has thus become an on-going research topic to facilitate the mass adoption of EV in coming decades.

Recent advances in sensing and control technologies envision demand response (DR) as an important tool to alleviate the electricity demand-supply mismatch issue. DR allows the energy users to reduce or shift their demand for electricity during peak periods in response to time-based rates or other form of financial incentive. In [2]–[4], different DR programs were proposed in residential household to provide the load shifting and curtailing of appliances. The benefits of DR programs in these studies could be undermined because the control of low power appliances has negligible impacts on the overall power consumption. Moreover, the load flexibility offered by some high power appliances could be restricted given that their operations are either non-shiftable or non-interruptible. Compared to the residential household, the coordination of large-scale EV charging in the parking station emerges as a more promising candidate for utility's demand response due to the following reasons. First, the aggregated charging loads of EVs in parking station could serves as a great amount of demand capacity resource to obtain the appreciable impact on DR program if these aggregated loads are properly coordinated. Second, the greater load flexibility of these EV charging loads with shiftable and interruptible characteristics ensures that the scheduling of EV charging coordinated with utility's DR programs could satisfy all charging demands of EVs while fulfilling committed demand curtailment for DR.

Although it was not explicitly mentioned, most EV charging scheduling were coordinated with the price-based DR programs offered by the utility as these massive charging loads were distributed to the off-peak time periods based on the dynamic electricity tariffs such as day-ahead pricing (e.g., [5] and [6]), real-time pricing (e.g., [7]–[10]), or time-of-use pricing [11]. This paper provides an insight into the potentials of executing both price-based and incentive-based DR programs in an EV parking station by harnessing the flexible characteristic of EV charging loads. A charging management system (CMS) is deployed to monitor and manage the EV charging operations. A real-time EV charging scheme is proposed in the CMS by combining the LP and convex relaxation method. Apart from keeping the total charging loads of parking station below a demand limit during the DR event, the proposed work also aims to maximize the number of EV for charging at each scheduling period and minimize the electricity bill based on the dynamic electricity tariff provided by utility. Notably, the proposed charging scheme leverages the benefit of on-off strategy to solve the EV charging problem. The on-off strategy tends to charge the selected EVs with faster rate by drawing the maximum charging power from charging pole, thus could fully charge the vehicles with less time. However, it is a non-trivial task to optimize the binary charging decision of each EV since the scheduling problem is formulated as a binary optimization problem. While the exhaustive search can be used to determine the optimal charging schedule, it is computationally expensive and not feasible for real-time implementation. A convex relaxation method is developed to overcome this difficulty by computing the near-optimal charging scheduling.

The technical novelty and main contributions of this paper are as follows:

1) A real-time EV charging scheme is proposed that not only coordinates the EV charging loads based on the dynamic electricity tariff, but also responses to the demand curtailment request from utility during the DR events.
2) An on-off strategy is used for EV charging scheduling, i.e., each EV is charged by a constant and maximum power drawn from the charging pole. The benefits of charging with on-off strategy instead of modulated power are as follows. First of all, it was suggested in [12] that charging the EV with a constant power could prolong the battery's service time. Secondly, smaller communication overheads are required to contact with a small subset of EVs and hence it is more practical to turn charging on or off rather than modulating the charging rate when a great amount of EV charging are scheduled [13]. Finally, it is expected that using on-off strategy can fully charge the EVs in shorter timeframe.
3) An optimization problem is formulated to maximize the number of EVs selected for charging at each time period. Since both of the EV charging priority and the preference of electricity price for charging are considered in the selection process, two contradict objectives of maximizing the EV owner's convenience in meeting all charging requests and minimizing the total electricity bill for the parking station are achieved.
4) The EV charging scheduling using on-off strategy is essentially a binary optimization problem that is difficult to be solved in real-time. To tackle this issue, an EV charging scheme that combines both linear programming and a modified convex relaxation scheme is proposed. Extensive simulation studies show that the proposed

TABLE I
COMPARISON OF PROPOSED WORK WITH OTHER EV CHARGING SCHEMES

Reference	Point of View	Objective Model	Optimization Method	Time horizon
Jin et al. [16]	Aggregator, EV owners	Max. aggregator's profit, Min. total charging cost	LP	Day-ahead (static) Real-time (dynamic)
Xu et al. [11]	DSO	Min. total electricity cost, Min. system peak load	LP	Day-ahead
Jin et al. [17]	Aggregator	Max. aggregator's revenue	MILP	Real-time
Ansari et al. [6]	Aggregator	Max. aggregator's profit	FLP	Real-time
Kuran et al. [18]	Parking station operator, EV owners	Max parking lot revenue or Max. total numbers of EVs fulfilling charging requirements	LP + first come first serve (or earliest deadline first)	Two-stage
He et al. [19]	EV owners	Min. total charging cost	QP	Two-stage
Jian et al. [20]	Grid operator	Min. overall load variance	QP	Day-ahead
Han et al. [21]	Aggregator, EV owners	Max. aggregator's profit	DP	Two-stage
Skugor and Deur [22]	Aggregator, EV owners	Min. total charging cost	DP	Day-ahead
Su et al. [7-9] and Rahman et al. [10]	Parking station operator, EV owners	Max. average SOC of all EVs at the next time step	Swarm intelligence	Real-time
Zhang and Li [23]	EV owners	Max. user utilization	Game theoretic	Day-ahead
Pipattanasomporn et al.[3]	Residential EV owners	Min. the violation of comfort setting	Scheduling algorithm	Real-time
Shao et al. [2]	DSO	Min. the EV charging impact	Scheduling algorithm	Real-time
Lausehammer [24]	Utility	Min. total electricity cost	Game theoretic	Day-ahead
Rassaei et al. [25]	Energy Retailer	Min. peak demand	LP	Day-ahead
Tan et al. [26]	Residential EV owners	Min. total electricity cost	ADMM	Day-ahead
Shafie-khah et al. [27]	Parking station operator	Max. profit	Stochastic programming	Day-ahead
Shafie-khah et al. [28]	EV aggregation agents	Max. profit	Stochastic programming	Day-ahead
Yazdani-Damavandi et al. [30]	Micro-MES operator	Max. profit	MILP	Day-ahead
Proposed work	Parking station operator, EV owners	Max. selected EV for charging, Min. total charging cost	LP + convex relaxation	Real-time

approach is able to solve the binary optimization problem in real-time with significantly reduced complexity than commercial optimization software.

The rest of this paper is organized as follows. Section II presents the related works. Section III describes the system model of an EV parking station. This is followed by Sections IV and V which present the formulation of EV charging problem and the application of convex relaxation to solve the charging problem efficiently, respectively. The computer simulations are presented in Section VI, and the conclusions are drawn in Section VII.

II. RELATED WORKS

Numerous optimization approaches have been proposed to address the EV charging scheduling problems such as those in [14] and [15] for the thorough surveys. Linear programming (LP) is a widely used solution method to optimize the EV charging. In [16], a LP model is defined to maximize the aggregator's profit and minimize the EV owner's charging cost. A hierarchical control scheme for EV charging across multiple aggregators was proposed in [11] to minimize the electricity cost and system peak load. Each aggregator's charging curve first is solved at the distribution system operator (DSO) level, followed by the power allocation of each EV using a heuristic algorithm. Both studies in [6] and [17] maximized the profits of aggregator using a mixed integer linear programming (MILP) and fuzzy linear programming (FLP) models, respectively. The fuzzy formulation of [6] was used to tackle the uncertainties of electricity market. The EV charging problem in [18] can be tackled from the perspective of parking station operator or EV owners using different LP formulations, i.e., to maximize the parking lot revenue or the numbers of complete charged EVs. Quadratic programming (QP) is another method used to pursue the charging schedules. In [19], the total charging cost of EV owners was minimized based on the dynamic electricity price using QP formulation. A double-layer optimization charging strategy was proposed in [20] using QP to minimize the load variance of grids. Dynamic programming (DP) was used in [21] and [22] to maximize the aggregator's profit and minimize the charging cost of EV owners, respectively. The computational load of DP in [22] was reduced by representing the EV fleet as an aggregated battery. Similar perspectives were also used in [7]–[10] to maximize the average state-of-charge (SOC) level of EVs with different swarm intelligence algorithms. The game theoretic method was used in [23] to maximize utilization of EV owners in the parking station without considering the stochastic factors of electricity tariff variations and the EV driving patterns.

The prominent demand elasticity offered by the EV charging load leads to the deployment of more enhanced DR strategies to improve load balancing of grids, while enabling the EV smart charging. Two DR techniques were proposed in [2] and [3] to shift and curtail the loads of high power household appliances (including EVs) based on the demand limits, user's priority, and comfort preference. A game theoretic based multi-agent DR simulation platform called Okeanos was used in [24] to analyze the benefits of optimal EV charging, revealing that the increasing of both feed-in tariff and EV penetration can reduce the utility bills. A distributed DR method considering the random usage patterns of EV was proposed in [25] using LP to minimize the peak demand of distribution grid. In [26], the energy storage capability of EVs was utilized by a distributed DR method derived using the alternating direction method of multiplier (ADMM) to minimize the user's bill.

Recently, the involvement of EV parking station in various DR programs were studied. In [27], the participation level of EV parking station in different price-based and incentive-based DR programs was optimized using a stochastic programming to maximize the operator's profit. Similar method was used in [28] to design a DR offering/bidding strategy that allows the parking station to take part in the intraday Demand Response eXchange (DRX) market [29] as an aggregation agent. The participation of parking station in DRX market enables it to supply energy with lower cost and offer higher capacity to reserve market, hence maximizing its profit. The energy storage capability of EV parking lots was utilized in [30] to model a multienergy system (MES), aiming to enhance the operational flexibility of MES and maximize the MES operator's profit.

In Table I, the proposed work is compared with other EV charging schemes by looking into 4 aspects including point of view, objective model, optimization method, and time horizon. The two-stage process in Table I refers to the process designed in both day-ahead and real-time time horizons. The difference between the proposed approach and previously reported works are summarized as follows:

1) The works in [7]–[10], [18] focused on the EV charging coordination, while those in [27], [28], and [30] optimized the amount of energy traded in different energy markets. The proposed work explores the role of EV parking station as both DR and charging service providers, aiming to optimize the individual charging schedule of each EV while being able to fulfill the demand curtailment request from utility.
2) Some previous works aimed to maximize the convenience of EV owners by fulfilling all charging requests (e.g., [7]–[10]) or minimize the charging cost (e.g., [19], [22], and [26]). A simple objective function is proposed herein to achieve both contradict purposes by considering both EV charging priority and preference of electricity price for charging as the coefficients in objective function. A delicate mechanism of sorting the decision variables based on EV charging priority is designed to speed up the optimization process.
3) The EV charging rate of most studies (e.g., [7]–[11], [16], [18], [19], [25], and [26]) were modulated as real-values. The proposed work employs the on-off strategy to schedule the EV scheduling, i.e., either charge the EV with maximum charging power or no charge at all.

III. Charging Electric Vehicles in Parking Station

As the number of EVs grows, more parking stations tend to install charging pole at every parking space. The charging poles cannot charge all connected EVs simultaneously due to the limitation of installation capacity of electric distribution system for the parking station. A charging scheduling scheme is thus required to coordinate charging among all EVs connected to charging poles so that the entire charging load of parking station remains below the installation capacity while satisfying charging requests of connected EVs before their departure. The arrival, departure time, and residual battery capacity of every EV are different. In addition to avoiding overload, the charging scheme determines the charging priorities of all connected EVs so that charging fairness and the need of providing enough energy for every EV's battery before departure are both satisfied. Assume that the EV charging in parking station is conducted in an environment with day-ahead electricity tariff. The charging scheduling also aims to minimize the electricity bill by choosing appropriate time slots to charge during EV's stay in the parking station. Charging a number of EVs at the same time in the parking station causes a large load for electric distribution system. However, the load can be leveled, delayed, or managed in an intelligent way. This makes the EV charging in parking station a good candidate for DR. Scheduling of EV charging can thus be coordinated with utility's DR.

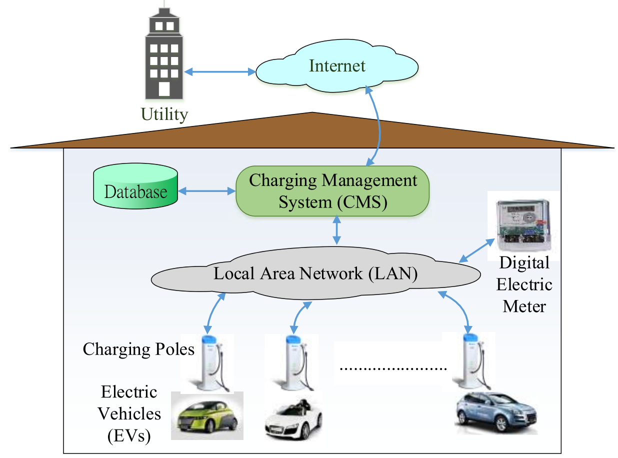

Fig. 1. System model of EV parking station that participates in the DR program.

In order to fulfill the above mentioned goals, a CMS is designed to optimize charging scheduling of electric vehicles in the parking station in response to utility company's DR requests in the day-ahead electricity tariff environment. As shown in Fig. 1, utility company's DR requests are sent to CMS through Internet. The meter installed at parking station returns the recorded electric load profile of electricity consumption back to utility via Internet. By reading the recorded load profile, the utility can verify if the parking station has fulfilled the committed demand curtailment during the DR events and calculate the electricity bill. The CMS monitors the status of each parking space and coordinates charging scheduling of every charging pole. Two-way communications between the CMS, charging poles, and database are established through a local area network (LAN) with communication media such as Wi-Fi, RS-485, or Ethernet.

It is assumed that the charging pole records EV's arrival time and every EV's driver key in estimated departure time into the charging pole. The CMS monitors occupation status of every parking space, the charging status and power consumption of every charging pole through LAN. In order to charge EV as fast as possible so that the rights of charging could be passed to more connected but uncharged EVs, charging is conducted with maximum charging power. In other words, all the charging poles are controlled by CMS through LAN to either charge with maximum power or no charge. As the rights of charging are passed faster among parked EVs, more EVs could finish charging in less time.

The demand elasticity offered by the EV charging loads of entire parking station can be leveraged to participate DR. The requests to participate DR are sent from the utility to CMS through Internet. The demand reduction committed by the parking station in response to participated DR event can either be fixed or time-varying. The demand curtailment profile scheduled by the parking station depends on the DR events such as the successful bids cleared in a day-ahead market for demand bidding program, the negotiated amounts agreed upon by the utility for interruptible load program, etc. Optimizing the scheduling of demand curtailment profile for DR has drawn wide research interests [31]–[33]. It will not be investigated in this paper. Instead, this paper mainly focuses on proposing a novel real-time optimization approach for EV charging scheduling in parking station under the condition that the demand curtailment profile is determined.

IV. Optimal Charging Scheduling

Suppose that a total of N charging poles are available in the parking station to provide the charging service for incoming EVs. An on-line optimization scheme will be proposed for the CMS to coordinate the charging scheduling for N charging poles. Although EVs arrive or leave the parking station continuously, the sampling interval is set to be T_s, i.e., the CMS optimizes the charging scheduling every T_s minutes. The total available time period H for charging during a day is evenly divided into J intervals where $J = H/T_s$. If the EV is connected to the *n-th* charging pole at the real-valued arrival time of t_n^{arr}, a sign-on status is initiated and the charging pole is considered activated. The arrival time step κ_n^{arr} is obtained by mapping the real value ratio t_n^{arr}/T_s onto the smallest following integer with the ceiling rounding operator $\lceil\cdot\rceil$, i.e., $\kappa_n^{arr} = \lceil t_n^{arr}/T_s \rceil$. Let the estimated real-valued departure time input by the driver at the *n-th* charging pole be t_n^{dep}. The associated departure time step κ_n^{dep} is obtained by mapping the real value ratio t_n^{dep}/T_s onto the largest previous integer using the floor rounding operator $\lfloor\cdot\rfloor$, i.e., $\kappa_n^{dep} = \lfloor t_n^{dep}/T_s \rfloor$.

A binary parameter δ_n^j is used to denote the connection status of each *n-th* charging pole at the *j-th* time step, $n = 1 \ldots N$ and $j = 1 \ldots J$. Specifically, $\delta_n^j = 1$ if the *n-th* charging pole is connected; $\delta_n^j = 0$ otherwise. A binary variable s_n^j is utilized to denote the charging status. If the charging pole is charging the parked EV, $s_n^j = 1$; otherwise $s_n^j = 0$. Note that s_n^j could be either 1 or 0 with $\delta_n^j = 1$ and $s_n^j = 0$ if $\delta_n^j = 0$.

While the proposed charging scheme is used for DR application in the EV parking station, it also aims to optimize the charging schedule by simultaneously maximizing the number of selected EVs for charging at each time step and minimizing the electricity bill paid to the utility under the variable electricity tariff. To achieve these objectives, two criteria known as the EV charging priority and the preference on electricity price are considered in selecting the optimal subset of all charging poles for charging at each time step.

A. EV Charging Priority and Preference

The charging priority for every *n-th* EV is governed by a weighting that integrates both capacity to refill for EV's battery and the remaining charging time. Denote γ_n^j as the SOC of EV connected to the *n-th* charging pole at the *j-th* time step and E_n^{cap} as the battery capacity of this EV. Let D_n^j be the remaining charging time steps of EV at the *j-th* time step, then

$$D_n^j = \kappa_n^{dep} - j. \tag{1}$$

Assume that the EV charged by the *n-th* charging pole has different membership ranking ψ_n, where $\psi_n \in [0, 1]$. The membership could be usually categorized into several levels and the membership belonging to higher levels corresponds to larger ψ_n but pay more membership fee and have higher priority in charging scheduling. For every *n-th* connected EV, no matter whether it is being charged or not, the weighting of charging priority at the *j-th* time step is defined as:

$$w_n^j = \begin{cases} \frac{\psi_n E_n^{cap}\left(\gamma^{\max} - \gamma_n^j\right)}{P_n^{\max} D_n^j}, & \text{if } \delta_n^j = 1; \\ 0, & \text{if } \delta_n^j = 0. \end{cases} \tag{2}$$

The numerator of (2) denotes the remaining battery capacity needs to be filled to battery's upper limit $\gamma^{\max}$, implying that the EVs with less SOC have more urgent charging needs. For every *n-th* charging pole, it is controlled to charge connected EV with maximum power $P_n^{\max}$. The denominator of (2) denotes the maximum charging energy that can be provided to the EV. The EVs with shorter D_n^j have more urgent charging needs and they need to be charged as much as possible prior to their departures. Note that $w_n^j \in [0, 1]$. The *n-th* charging pole is set to the sign-off mode and both the weighting w_n^j and the parking space occupation status δ_n^j are both reset to 0 when the connected EV is disconnected from it and leave the parking station $\forall n = 1 \ldots N, j = 1 \ldots J$. The charging pole is activated again when a new EV connects with it at the later time steps and the associated weighting w_n^j is recalculated using (2).

While it is crucial to satisfy the EV charging demands, it is also economically desirable to minimize the electricity bill by exploiting the dynamic characteristic of electricity tariff. More connected EVs should be selected for charging at the time periods of lower electricity prices and vice versa. Denote $\alpha_{\max}$ and $\alpha_{\min}$ as the maximum and minimum electricity prices offered by the utility, respectively. Let ρ_n^j be an auxiliary parameter used to quantify the preference level of the *n*-th charging pole to perform charging at the *j-th* time step with the electricity price α^j, then

$$\rho_n^j = \frac{\left(\alpha_{\max} - \alpha^j\right)}{\left(\alpha_{\max} - \alpha_{\min}\right)}, \forall n = 1 \ldots N, j = 1 \ldots J. \tag{3}$$

According to (3), the preference term ρ_n^j returns a higher value in response to the lower electricity price α^j and vice versa. The term in the denominator of (3) is to normalize $\rho_n^j \in [0, 1]$.

B. Scheduling Optimization

An optimal charging scheduling is proposed to coordinate the charging process of all the connected EVs at each *j-th* time step and keep the total charging load below certain demand limit based on the charging priority w_n^j and preference on the electricity price ρ_n^j. Define a set $\Psi^j = \{w_1^j, w_2^j, \ldots, w_N^j\}$ to store the weighting terms of all charging poles at the *j-th* time step where w_n^j is defined as in (2). Let C be a set containing all indices of charging poles, i.e., $C = \{1, \ldots, N\}$. In the optimal scheduling scheme to be defined later, the charging pole is evaluated one by one for charging right in the searching process of optimization. The total charging load is constrained by the capacity limit available for EV and the demand curtailment due to DR. The scheduling optimization is designed to conduct the searching for optimal set of charging poles to fit the objective function while satisfying constraints. The searching is designed according to the descending order of weightings w_n^j. Define $Perm(\cdot)$ as a permutation operator used to sort the elements in a given set in descending order. The elements in C are rearranged based on the descending order of w_n^j collected from Ψ^j using $Perm(\cdot)$ at every *j-th* time step. These sorted charging pole indices are stored in a new set Γ^j defined as:

$$\Gamma^j = Perm(C)\big|_{\Psi^j}. \tag{4}$$

The scheduling optimization is designed to maximize the number of selected EVs for charging at each time step. The objective function to be maximized at the current *k-th* time step is formulated as the products of charging priorities w_n^i and preference on electricity prices ρ_n^i evaluated from the current *k-th* time step to the end of day. Therefore, the objective function for maximization is defined as:

$$\max_{s_n^j, j=k,\ldots,J} \sum_{i=j}^{J} \sum_{n\in\Gamma^j} s_n^i w_n^i \rho_n^i. \tag{5}$$

Referring to (5), the optimal charging scheduling is to maximize the number of EV for charging at each scheduling period and minimize the electricity bill based on the dynamic electricity tariff provided by utility. If the electricity price α^j is directly included in (5) for maximization, the electricity bill for charging in the parking station will be maximized and it is against the goal of optimal charging scheduling. Therefore, an auxiliary variable ρ_n^j is defined as in (3) so that the electricity bill can be minimized by using the maximization scheme in (5).

It is shown in (5) that the searching order of all charging poles for the maximization of objective function is determined by the permuted set Γ^j in (4). The charging poles with larger weightings are assigned higher priorities to be chosen for charging because the indices of charging poles in Γ^j is rearranged in descending order of weightings according to (4).

Although the EV connected to the *n-th* charging pole only stays at the parking space for the time steps $j \in [\kappa_n^{arr}, \kappa_n^{dep}]$, the charging scheduling optimization can be made from the current *k-th* time step to the end of day, i.e., $j \in [k, J]$ for the convenience of calculation due to the fact that $w_n^j = 0, \forall j \in [\kappa_n^{dep}, J]$ as defined in (2).

Let P_{total} be the capacity limit available for EV charging in the parking station without considering DR programs, P_{DR}^j be the demand curtailment for DR program at every *j-th* time step. The total charging load is constrained by the demand limit $(P_{total} - P_{DR}^j)$ at every *j-th* time step. Therefore,

$$\sum_{n\in\Gamma^j} s_n^j P_n^{\max} \le P_{total} - P_{DR}^j, j = k \ldots J. \tag{6}$$

The charging of every EV needs to guarantee the minimum energy requirement for every EV's next traveling. Therefore, the SOC of the EV charged by the *n-th* charging pole at the *j-th* time step, γ_n^j, is constrained by a lower limit $\gamma^{\min}$. Similarly, the SOC of the EV is also restricted by an upper limit $\gamma^{\max}$ to avoid overcharge. Let η be the charging efficiency, the charging of every EV are then constrained as:

$$\gamma_n^j E_n^{cap} + \eta P_n^{\max} s_n^j T_s \ge \gamma^{\min} E_n^{cap}, j = k \ldots J; \tag{7}$$

$$\gamma_n^j E_n^{cap} + \eta P_n^{\max} s_n^j T_s \le \gamma^{\max} E_n^{cap}, j = k \ldots J. \tag{8}$$

The SOC of EV's battery at every time step is updated as:

$$\gamma_n^{j+1} = \gamma_n^j + \frac{\eta P_n^{\max} s_n^j T_s}{E_n^{cap}}. \tag{9}$$

V. Convex Relaxation

The optimization in (5)-(8) is a binary programming because the decision variables $s_n^j \in \{0, 1\}, n = 1 \ldots N, j = 1 \ldots J$. The binary optimization is computationally expensive and suffers from curse of dimensionality. Either large N or J in (5) could easily lead the optimization to be an oversized unsolvable problem. Thus, binary optimization in (5)-(8) is not feasible to solve the charging scheduling problem in real time. A convex relaxation method [34], [35] is proposed to address this issue.

The binary decision variable $s_n^j \in \{0, 1\}$ of (5)-(8) is first relaxed to allow for the real-value charging decision $\hat{s}_n^j \in [0, 1]$. The binary programming problem in (5)-(8) can be approximated by solving a LP problem as follows:

$$\max_{\hat{s}_n^j, j=k,\ldots,J} \quad \sum_{i=j}^{J} \sum_{n\in\Gamma^j} \hat{s}_n^i w_n^i \rho_n^i \tag{10}$$

$$\text{subject to} \quad \sum_{n\in\Gamma^j} \hat{s}_n^j P_n^{\max} \le P_{Total} - P_{DR}^j, j = k \ldots J. \tag{11}$$

$$\gamma_n^j E_n^{cap} + \eta P_n^{\max} \hat{s}_n^j T_s \ge \gamma^{\min} E_n^{cap}, j = k \ldots J. \tag{12}$$

$$\gamma_n^j E_n^{cap} + \eta P_n^{\max} \hat{s}_n^j T_s \le \gamma^{\max} E_n^{cap}, j = k \ldots J. \tag{13}$$

In essence, LP is computationally efficient and not bothered by dimensionality, therefore it is suitable for the real-time scheduling of EV charging. However, the relaxed optimization variables $\hat{s}_n^j$ obtained from (10)-(13) are fractional values within the range 0 to 1 and need to be mapped into 0 or 1 to realize the on-off strategy of the proposed work. In other words, a mapping from $\hat{s}_n^j \in [0, 1]$ to $s_n^j \in \{0, 1\}$ is required. Moreover, the mapping results s_n^j need to also satisfy the constraints in (6)-(8). Although both the floor and ceiling rounding operators are easy to implement, they are not applicable for the mapping. The mapping $s_n^j = \lfloor \hat{s}_n^j \rfloor$ produced by the floor-rounding is conservative because only a small subset of EVs are selected for charging. On the contrary, the mapping $s_n^j = \lceil \hat{s}_n^j \rceil$ produced by the ceiling-rounding could violate the constraints (6)-(8) because this method tends to select excessive number of EVs for charging. A two-stage processing is proposed to tackle the aforementioned difficulties.

Let $\hat{\mathbb{S}}^k \in R^{N\times(J-k+1)}$ be a matrix containing decision variables $\hat{s}_n^j, n = 1\dots N, j = k\dots J$, obtained from (10)-(13) by LP:

$$\hat{\mathbb{S}}^k = \begin{bmatrix} \hat{s}_1^k & \hat{s}_1^{k+1} & \cdots & \hat{s}_1^J \\ \hat{s}_2^k & \hat{s}_2^{k+1} & \cdots & \hat{s}_2^J \\ \vdots & \vdots & \ddots & \vdots \\ \hat{s}_N^k & \hat{s}_N^{k+1} & \cdots & \hat{s}_N^J \end{bmatrix} = \begin{bmatrix} \left(\hat{\mathbf{s}}_1^k\right)^T \\ \vdots \\ \left(\hat{\mathbf{s}}_N^k\right)^T \end{bmatrix}, \tag{14}$$

where $\hat{\mathbf{s}}_n^k = [\hat{s}_n^k, \dots, \hat{s}_n^J]^T, n = 1\dots N$. Let q_n^k be the number of time steps required to fully charge the EV connected to the *n-th* charging pole from the current *k-th* time step to end of day so that associated SOC $\gamma_n^k = \gamma^{max}$. Using the floor rounding operator $\lfloor\cdot\rfloor$, q_n^k can be defined as:

$$q_n^k = \left\lfloor \frac{E_n^{cap}\left(\gamma^{\max} - \gamma_n^k\right)}{\eta P_n^{\max} T_s} \right\rfloor. \tag{15}$$

The first stage of rounding scheme for convex relaxation is to map the fractional elements in $\hat{\boldsymbol{s}}_n^k$ to 0 or 1 while ensuring every EV is fully charged prior to departure. Denote the first rounding scheme by an operator $\Lambda_1(\boldsymbol{s}_{temp}, q_{temp})$ that maps the q_{temp} largest elements of vector $\boldsymbol{s}_{temp} \in R^{(J-k+1)\times 1}$ to 1 and maps the rest elements to 0. If $\tilde{\boldsymbol{s}}_n^k$ is the mapping result of the operator $\Lambda_1(\cdot,\cdot)$, then

$$\tilde{\boldsymbol{s}}_n^k = \Lambda_1\left(\hat{\boldsymbol{s}}_n^k, q_n^k\right), n = 1\dots N, \tag{16}$$

where the element $\tilde{s}_n^j \in \{0, 1\}\ \forall \tilde{s}_n^j \in \tilde{\boldsymbol{s}}_n^k, j = k\dots J$.

It is possible that the constraints in (6) are violated after first stage of rounding. A second stage of processing is thus required to ensure the relaxed optimization variables also satisfy the constraint in (6) at every time step. Denote $\tilde{\mathbb{S}}^k \in R^{N\times(J-k+1)}$ as the matrix containing all vectors $\tilde{\boldsymbol{s}}_n^k$, $n = 1\dots N$, i.e.,

$$\begin{aligned}\tilde{\mathbb{S}}^k &= \begin{bmatrix} \tilde{s}_1^k & \tilde{s}_1^{k+1} & \cdots & \tilde{s}_1^J \\ \tilde{s}_2^k & \tilde{s}_2^{k+1} & \cdots & \tilde{s}_2^J \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{s}_N^k & \tilde{s}_N^{k+1} & \cdots & \tilde{s}_N^J \end{bmatrix} = \begin{bmatrix} \left(\tilde{\mathbf{s}}_1^k\right)^T \\ \vdots \\ \left(\tilde{\mathbf{s}}_N^k\right)^T \end{bmatrix} \\ &= \left[\tilde{\boldsymbol{\omega}}^k, \tilde{\boldsymbol{\omega}}^{k+1}, \dots, \tilde{\boldsymbol{\omega}}^J\right], \end{aligned} \tag{17}$$

where $\tilde{\boldsymbol{\omega}}^j = [\tilde{s}_1^j, \tilde{s}_2^j, \dots, \tilde{s}_N^j]^T, j = k\dots J$. The vector of binary optimization variables $s^j \equiv [s_1^j, s_2^j, \dots, s_N^j]^T$ in (5) is updated as the vector $\tilde{\boldsymbol{\omega}}^j$ if the constraints in (6) is satisfied, i.e.,

$$s^j = \tilde{\boldsymbol{\omega}}^j, \text{if} \sum_{n\in\Gamma^j} \tilde{s}_n^j P_n^{max} \le P_{total} - P_{DR}^j, j = k\dots J. \tag{18}$$

However, if the constraints in (6) is not satisfied, the second stage of processing is designed to find the largest number of charging poles h^j to charge EVs while the constraints in (7)-(8) are still satisfied. Since the elements $\tilde{s}_n^j$ of $\tilde{\boldsymbol{\omega}}^j$ are either 0 or 1, it might search more than h^j elements from the first element onward before h^j nonzero elements (or 1s) are accumulated. Let the number of elements to search be g^j. Note that $g^j \ge h^j$. Taking g^j as an auxiliary optimization variable, h^j can be calculated by the following optimization.

$$\arg\max_{g^j} \left(\sum_{n=1}^{g^j} \tilde{s}_n^j P_n^{\max}\right) \tag{19}$$

$$\text{subject to} \sum_{n=1}^{g^j} \tilde{s}_n^j P_n^{\max} \le P_{total} - P_{DR}^j, j = k\dots J. \tag{20}$$

After g^j is obtained by (19)-(20), h^j is calculated as:

$$h^j = \sum_{n=1}^{g^j} \tilde{s}_n^j. \tag{21}$$

Note that h^j is only calculated under the condition that

$$\sum_{n\in\Gamma^j} \tilde{s}_n^j P_n^{max} > P_{total} - P_{DR}^j. \tag{22}$$

Denote the second stage of processing by an operator $\Lambda_2(\cdot,\cdot)$ that keeps h^j elements of vectors $\tilde{\boldsymbol{\omega}}^j$ in (17) to be 1 and converts the rest of elements to be 0. Then,

$$\Lambda_2\left(\boldsymbol{\omega}^j, h^j\right) = \left[\tilde{\mathrm{s}}_{top}^j, \mathbf{0}_{bot}\right]^T, \tag{23}$$

where $\tilde{\boldsymbol{s}}_{top} \in R^{g^j\times 1}$ but the elements in $\tilde{\boldsymbol{s}}_{top}$ satisfy the condition in (22) and $\mathbf{0}_{bot} = [0, 0, \dots, 0]^T \in R^{(N-g^j)\times 1}$. Referring to (18) and (23), vectors of binary optimization variables obtained from the LP and convex relaxation are defined as:

$$\boldsymbol{s}^j = \begin{cases} \tilde{\boldsymbol{\omega}}^j, & \text{if} \sum_{n\in\Gamma^j} \tilde{s}_n^j P_n^{\max} \le P_{total} - P_{DR}^j \\ \Lambda_2\left(\tilde{\boldsymbol{\omega}}^j, h^j\right), & \text{otherwise} \end{cases}, j = k\dots J. \tag{24}$$

The SOC of each EV is updated according to (9) as soon as s^j is calculated using (24) at each time step.

VI. Computer Simulations

A. Simulation Settings

A parking station with $N = 200$ charging poles are used in the following simulations to evaluate the performance of the proposed work. The total available time period H for charging is 24 hours and the sampling interval T_s for calculating optimal charging scheduling is set to 15 minutes. Therefore, the total number of time steps $J = H/T_s = 96$. The SOC upper and lower limits, i.e., $\gamma^{\max}$ and $\gamma^{\min}$, for every EV are set as 0.99 and 0.6, respectively. The day-ahead electricity prices shown in [36] are utilized for the simulation.

Both regular and random arrival EVs are considered for more realistic modeling of parking station utilization and the ratio is set as 7:3. Regular EVs have predictable habits of using the parking station due to their relatively fixed arrival and departure times. A Gaussian model is used to generate the arrival and departure times of regular EVs, where the arrival times follow a normal distribution with mean $\mu_{arv} = $ 6:00AM and standard deviation $\sigma_{arv} = 60$ minutes. The departure times are modeled with a normal distribution with $\mu_{dep} = $ 6:00PM and $\sigma_{dep} = 120$ minutes. The random arrival EVs have more

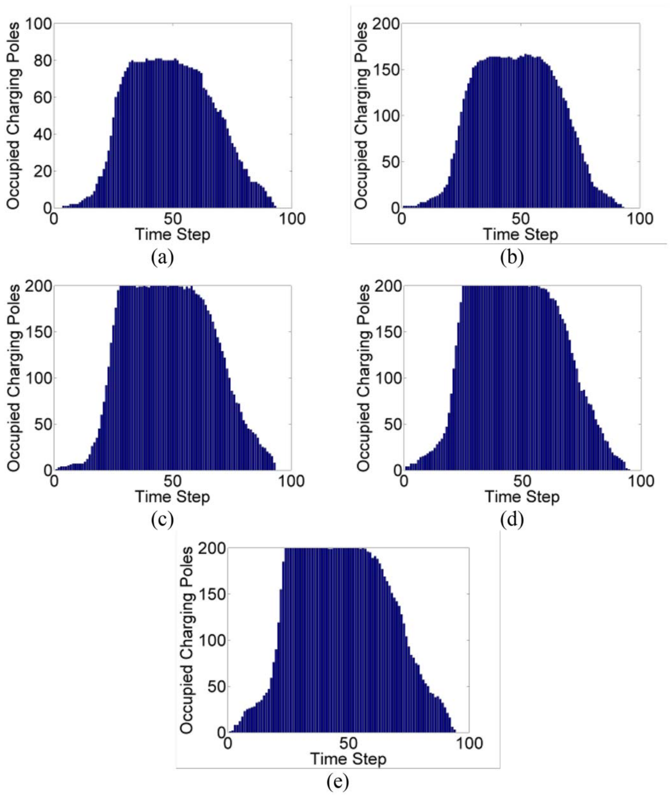

Fig. 2. Charging pole accommodation status for (a) $M = 100$, (b) $M = 200$, (c) $M = 300$, (d) $M = 400$, and (e) $M = 500$.

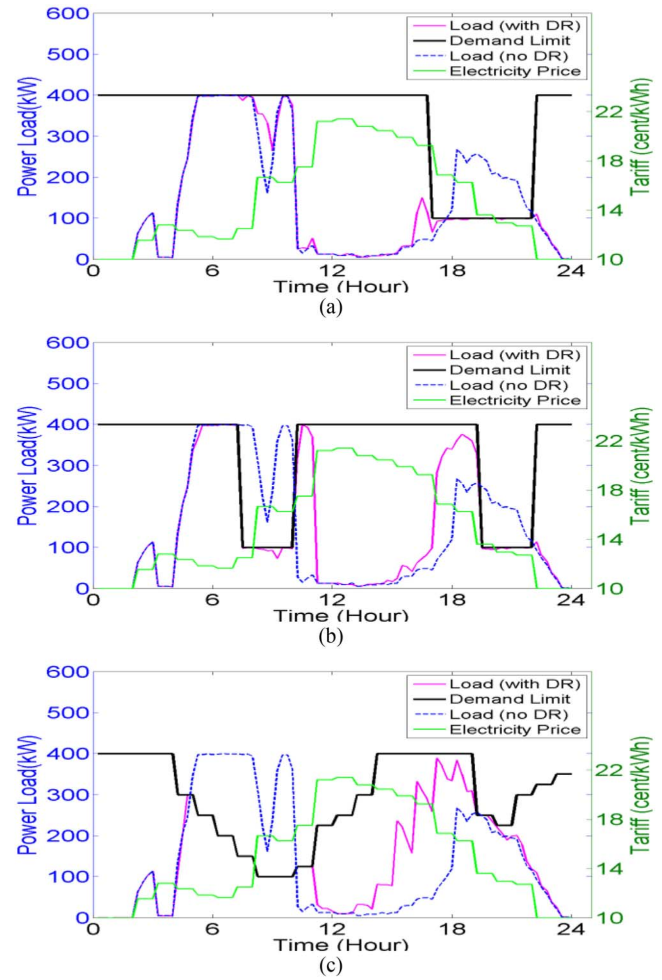

Fig. 3. Load profiles for 3 DR events. (a) constant load shedding in one longer period. (b) constant load shedding in two shorter periods. (c) time-varying load shedding in two different periods.

unpredictable habits of using the parking station due to their uncertain staying times. Their arrival and departure times are uniformly distributed along the scheduling period $j \in [1, J]$ to simulate the random utilization habits. Let M be the total number of EVs entering the parking station accumulated in the entire day, i.e., for the time steps $j = 1 \dots J$. Note that it is possible that one charging pole can serve more than one EV within a day. As the EV finishes charging and leaves the parking space, other EVs could reuse the charging pole. M is set to be 100, 200, 300, 400, to 500 for simulations. With the number charging poles (or parking spaces) $N = 200$, variations of number of EVs for the time steps $j = 1 \dots J$ are simulated in Fig. 2(a)-2(e). Note that as M increases to 300 or above, the parking station is full for several time steps.

The EVs with four types of battery capacities, i.e., 8kWh, 17kWh, 18kWh, and 48kWh are used and their proportions are set as 20%, 30%, 30%, and 20% of the M EVs, respectively. The maximum charging power drawn by these EVs are 1.6kW, 3.4kW, 3.6kW, and 9.6kW, respectively. Our study considers the Level 2 standard charging instead of Level 3 fast charging because using the latter method tends to compromise the battery's lifespan more rapidly [37]. The initial SOC of each EV is uniformly distributed in the range of [0.2, 0.5], while the charging efficiency η is set as 0.9. The proportions of EVs with the low, medium, and high membership rankings are set as 20%, 50%, and 30% of the M EVs, respectively. The capacity limit P_{total} of parking station is set as 400kW. All simulations are made using Matlab 2014a on the personal computer with Intel ® Core i5-4570 CPU @3.40GHz.

B. Simulation of Optimal Charging Scheduling

Three DR events are simulated verifying the proposed optimal scheduling approach in accordance with a variable day-ahead electricity tariff for $M = 500$. Fig. 3(a) shows that a long period of constant 300 kW load shedding DR event is requested from 17:00 to 22:00. Two shorter periods of constant 300 kW load shedding DR events are simulated in Fig. 3(b) from 7:30 to 10:00 and 19:30 to 22:00, respectively. A more complicated simulation is made in Fig. 3(c) where two time-varying load shedding DR events are requested starting from 5:00 to 14:00 and 20:00 and 24:00, respectively.

It is shown in Figs. 3(a)-3(c) that the optimal charging scheduling arranged by the proposed work is able to arrange the charging so that the overall load profile does not exceed the demand limit for different DR events. Moreover, the optimal charging scheduling prevents the EV charging at the periods of high electricity tariff to minimize the electricity bill.

C. Comparisons With Other Charging Schemes

The proposed approach is compared with the intuitive first come first serve (FCFS) strategy and LP based real-valued

TABLE II
COMPARISONS OF FINAL AVERAGE SOC γ^f_{avg}.

M	100	200	300	400	500
FCFS	0.99	0.99	0.98	0.96	0.96
LPRP	0.99	0.99	0.99	0.99	0.99
LPB&B	0.96	0.96	0.96	0.96	0.96
LPB&C	0.97	0.97	0.97	0.96	0.96
Proposed	0.99	0.99	0.99	0.99	0.99

charging power (LPRP) approach in order to verify its optimization capability. The proposed optimal charging scheduling scheme overcomes the binary optimization scheme by using LP with modified convex relaxation method. To verify the effectiveness and efficiency of the modified convex relaxation method, the proposed approach is also compared with the approach LP with more delicate convex relaxation methods such as branch and bound algorithm [38] (LPB&B) and branch and cut algorithm [39] (LPB&C). LPB&B is implemented using Matlab Optimization Toolbox while LPB&C is implemented using CPLEX12.1.

Let γ^f_{avg} be the average SOC of all vehicles leaving parking station at every time step. Comparison of γ^f_{avg} due to 5 different approaches for $M = 100$ to 500 are made in Table II. A notable decrement of γ^f_{avg} is shown by FCFS when M increases due to its tendency to allocate charging scheduling to the EVs with earlier arrival times. Both of the LPRP and the proposed approaches lead to the highest γ^f_{avg} for $M = 100$ to 500.

Let τ^f_{avg} be the average charging time steps to attain EV's final SOC. Comparison of τ^f_{avg} due to 5 different approaches are made in Table IV. Since LPB&B, LPB&C and proposed approach are essentially LP based binary optimization approach with convex relaxation method, these 3 approaches result in less τ^f_{avg} than LPRP as shown in Table IV. FCFS does not optimize scheduling and results in least τ^f_{avg} although it results in least γ^f_{avg} and most electricity bill. Table IV especially shows that the proposed approach charges EVs with either maximum power $P^{\max}$ or 0 could greatly reduce charging time compared to LPRP that charges EVs with modulated real-valued power. Recall that the sampling interval $T_s = 15$ minutes, the proposed approach saves 129.9 minutes to attain the same γ^f_{avg} than the LPRP for M = 500. The sooner the charging is completed, more parking spaces can be released after EVs completing their charging. Therefore, the proposed approach is more suitable to the public parking station.

It is shown in Tables II, III and IV that the proposed approach shows good optimization capability because it greatly outperforms FCFS. The modified convex relaxation method used in the proposed approach also shows its effectiveness and efficiency because the proposed approach results in similar optimization outcomes compared to commercial optimization tools such as LPB&B and LPB&C.

Finally, denote τ^{comp}_{avg} as the average computation time for different approaches. Comparison of τ^{comp}_{avg} due to 5 different approaches for $M = 100$ to 500 is made in Table V. The computation time is close to the time due to LPRP and much shorter than both LPB&B and LPB&C. Although LPRP is the approach without convex relaxation, it takes slightly more than the proposed approach because it takes more computation time for scheduling due to charging EVs with continuous real-valued power. Moreover, Table V also shows that the modified relaxation method results in much less computation time than the conventional approaches such as branch and bound, and branch and cut algorithms. It is also noted that increment of computation time with M due to the proposed approach is less than the ones due to LPB&B and LPB&C.

TABLE III
COMPARISONS OF ELECTRICITY BILLS ($/DAY) AND COST SAVING (%)

M	100	200	300	400	500
FCFS	1,578 (-)	3,586 (-)	4,338 (-)	4,368 (-)	4,377 (-)
LPRP	1,352 (↓14.32%)	3,111 (↓13.24%)	4,016 (↓7.42%)	3,966 (↓9.20%)	4,073 (↓6.94%)
LPB&B	1,321 (↓16.28%)	3,081 (↓14.08%)	3,903 (↓10.02%)	4,062 (↓7.00%)	4,000 (↓8.61%)
LPB&C	1,315 (↓16.66%)	3,008 (↓16.11%)	3,959 (↓8.73%)	3,972 (↓9.06%)	4,062 (↓7.19%)
Proposed	1,357 (↓14.00%)	3,126 (↓12.83%)	3,984 (↓8.16%)	4,008 (↓8.24%)	4,059 (↓7.27%)

TABLE IV
COMPARISONS OF AVERAGE TIME STEPS τ^f_{avg} TO ATTAIN THE FINAL SOC

M	100	200	300	400	500
FCFS	29.07	17.39	17.46	18.28	17.73
LPRP	42.18	44.15	43.93	43.39	43.64
LPB&B	33.66	36.70	34.97	36.61	34.65
LPB&C	33.53	36.09	35.70	35.61	34.73
Proposed	34.18	36.56	35.82	36.28	34.98

TABLE V
COMPARISONS OF AVERAGE COMPUTATION TIME τ^{comp}_{avg} (SECONDS)

M	100	200	300	400	500
FCFS	0.09	0.12	0.14	0.14	0.15
LPRP	0.12	0.19	0.22	0.22	0.22
LPB&B	7.83	19.45	22.81	25.43	29.09
LPB&C	0.18	5.99	8.40	10.10	18.38
Proposed	0.11	0.16	0.18	0.19	0.19

VII. CONCLUSION

A real-time charging scheme for DR application in an EV parking station has been proposed. The proposed work aims to simultaneously maximize the number of selected EVs for charging and minimize the electricity bill paid to the utility. Since the proposed optimal charging scheduling scheme is designed for the use in real-time, a relatively simple objective function is developed. The on-off strategy is leveraged by the proposed work to achieve the fast charging speed of EVs and this leads to the formulation of a computationally expensive binary optimization problem. A modified convex relaxation method is developed to overcome this difficulty by computing the near-optimal charging schedules. The modification of convex relaxation method is also computationally effective and suitable for real-time calculation.

The proposed real-time optimal charging scheduling scheme is designed for the operator of parking station so that the parking stating could schedule the charging of every EV at the time steps with lower dynamic electricity prices while satisfying EV owners' charging needs. At the same time, the operator of parking station could even take part in the DR event and get further rewarded from utility by making constant or time-varying demand curtailment. Once the demand curtailment is determined for DR, the proposed optimal charging scheduling scheme could arrange the charging scheduling so that the total demand is constrained by the predetermined demand limit.

REFERENCES

[1] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011.

[2] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid integration of electric vehicles and demand response with customer choice," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 543–550, Mar. 2012.

[3] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2166–2173, Dec. 2012.

[4] S. Zhou, Z. Wu, J. Li, and X.-P. Zhang, "Real-time energy control approach for smart home energy management system," *Elect. Power Compon. Syst.*, vol. 42, nos. 3–4, pp. 315–326, Feb. 2014.

[5] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 131–138, Mar. 2011.

[6] M. Ansari, A. T. Al-Awami, E. Sortomme, and M. A. Abido, "Coordinated bidding of ancillary services for vehicle-to-grid using fuzzy optimization," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 261–270, Jan. 2015.

[7] W. Su and M.-Y. Chow, "Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck," *Appl. Energy*, vol. 96, pp. 171–182, Aug. 2012.

[8] W. Su and M.-Y. Chow, "Performance evaluation of a PHEV parking station using particle swarm optimization," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, San Diego, CA, USA, Jul. 2011, pp. 1–6.

[9] W. Su and M.-Y. Chow, "Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 308–315, Mar. 2012.

[10] I. Rahman, P. M. Vasant, B. S. M. Singh, and M. Abdullah-Al-Wadud, "On the performance of accelerated particle swarm optimization for charging plug-in hybrid electric vehicles," *Alexandria Eng. J.*, vol. 55, no. 1, pp. 419–426, Mar. 2016.

[11] Z. Xu, Z. Hu, Y. Song, W. Zhao, and Y. Zhang, "Coordination of PEVs charging across multiple aggregators," *Appl. Energy*, vol. 136, pp. 582–589, Dec. 2014.

[12] Q. Huang, Q.-S. Jia, Z. Qiu, X. Guan, and G. Deconinck, "Matching EV charging load with uncertain wind: A simulation-based policy improvement approach," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1425–1433, May 2015.

[13] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, "Demand dispatch," *IEEE Power Energy Mag.*, vol. 8, no. 3, pp. 20–29, May/Jun. 2010.

[14] W. Su, H. Eichi, W. Zeng, and M.-Y. Chow, "A survey on the electrification of transportation in a smart grid environment," *IEEE Trans. Ind. Informat*., vol. 8, no. 1, pp. 1–10, Feb. 2012.

[15] J. C. Mukherjee and A. Gupta, "A review of charge scheduling of electric vehicles in smart grid," *IEEE Syst. J.*, vol. 9, no. 4, pp. 1541–1553, Dec. 2015.

[16] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging: A customer's perspective," *IEEE Trans. Veh. Technol*., vol. 62, no. 7, pp. 2919–2927, Sep. 2013.

[17] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging with energy storage in the electricity market," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 311–320, Mar. 2013.

[18] M. S. Kuran *et al.*, "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.

[19] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1095–1105, Sep. 2012.

[20] L. Jian, X. Zhu, Z. Shao, S. Niu, and C. C. Chan, "A scenario of vehicle-to-grid implementation and its double-layer optimal charging strategy for minimizing load variance within regional smart grids," *Energy Convers. Manag.*, vol. 78, pp. 508–517, Feb. 2014.

[21] S. Han, S. Han, and K. Sezaki, "Development of an optimal vehicle-to-grid aggregator for frequency regulation," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 65–72, Jun. 2010.

[22] B. Škugor and J. Deur, "Dynamic programming-based optimisation of charging an electric vehicle fleet system represented by an aggregate battery model," *Energy*, vol. 92, pp. 456–465, Dec. 2015.

[23] L. Zhang and Y. Li, "A game-theoretic approach to optimal scheduling of parking-lot electric vehicle charging," *IEEE Trans. Veh. Technol*., vol. 65, no. 6, pp. 4068–4078, Jun. 2016.

[24] W. Lausenhammer, D. Engel, and R. Green, "Utilizing capabilities of plug in electric vehicles with a new demand response optimization software framework: Okeanos," *Int. J. Elect. Power Energy Syst.*, vol. 75, pp. 1–7, Feb. 2016.

[25] F. Rassaei, W.-S. Soh, and K.-C. Chua, "Demand response for residential electric vehicles with random usage patterns in smart grids," *IEEE Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1367–1376, Oct. 2015.

[26] Z. Tan, P. Yang, and A. Nehorai, "An optimal and distributed demand response strategy with electric vehicles in the smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 861–869, Mar. 2014.

[27] M. Shafie-Khah *et al.*, "Optimal behavior of electric vehicle parking lots as demand response aggregation agents," *IEEE Trans. Smart Grid*, to be published.

[28] M. Shafie-Khah *et al.*, "Optimal trading of plug-in electric vehicle aggregation agents in a market environment for sustainability," *Appl. Energy*, vol. 162, pp. 601–612, Jan. 2016.

[29] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, "The role of aggregators in smart grid demand response markets," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1247–1257, Jul. 2013.

[30] M. Yazdani-Damavandi, M. P. Moghaddam, M.-R. Haghifam, M. Shafie-Khah, and J. P. S. Catalão, "Modeling operational behavior of plug-in electric vehicles' parking lot in multienergy systems," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 124–135, Jan. 2016.

[31] D. Menniti, F. Costanzo, N. Scordino, and N. Sorrentino, "Purchase-bidding strategies of an energy coalition with demand-response capabilities," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1241–1255, Aug. 2009.

[32] E. Campos-Nanez, N. Fabra, and A. Garcia, "Dynamic auctions for on-demand services," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 37, no. 6, pp. 878–886, Nov. 2007.

[33] D. T. Nguyen, M. Negnevitsky, and M. de Groot, "Walrasian market clearing for demand response exchange," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 535–544, Feb. 2012.

[34] H. D. Sherali and W. P. Adams, *A Reformulation-Linearization Technique for Solving Discrete and Continuous Nonconvex Problems.* Dordrecht, The Netherlands: Kluwer Academic, 1999.

[35] C. A. Floudas, *Deterministic Global Optimization: Theory, Methods and Applications*. Dordrecht, The Netherlands: Kluwer Academic, 2000.

[36] *Réseau de Transport D'électricité*. Accessed on May 7, 2015. [Online]. Available: http://clients.rte-france.com/index_en.jsp

[37] A. Hess *et al.*, "Optimal deployment of charging stations for electric vehicular networks," in *Proc. 1st Workshop Urban Netw*., Nice, France, Dec. 2012, pp. 1–6.

[38] E. L. Lawler and D. E. Wood, "Branch-and-bound methods: A survey," *Oper. Res.*, vol. 14, no. 4, pp. 699–719, Aug. 1966.

[39] M. Padberg and G. Rinaldi, "A branch-and-cut algorithm for the resolution of large-scale symmetric traveling salesman problems," *SIAM Rev.*, vol. 33, no. 1, pp. 60–100, Mar. 1991.

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