

Constructing a V2G-enabled Regional Energy Internet for Cost-efficient Carbon Trading

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Abstract—The increasing penetration of plug-in electric vehicles (PEVs) has highlighted the importance of coordinating ubiquitous distributed energy resources (DERs) via the internet of things (IoT). With the help of vehicle-to-grid (V2G) technology, PEVs can be aggregated to behave as a storage system, yielding both economic and environmental benefits. In this paper, we propose an optimal bidding framework for a V2G-enabled regional energy internet (REI) to participate in day-ahead markets considering carbon trading. The REI operator aims to maximize the net profits from day-ahead markets while anticipating real-time adjustments. A detailed battery model is developed to depict the charging and discharging capability of V2G-enabled PEVs. A two-stage stochastic optimization model is formulated to schedule the operation of PEV fleets against various sources of uncertainties, e.g., the arrival and departure time of PEVs, solar power and real-time prices. Case studies undertaken based on realistic datasets demonstrate that the coordination of the V2G-enabled PEVs and other DERs can facilitate the accommodation of renewable energy, thus improving the REI's revenues in energy and carbon markets.

Index Terms—Carbon trading, internet of things, market bidding, regional energy internet, vehicle-to-grid.

I. INTRODUCTION

IN recent years, the concept of the energy network has aroused the attention and interest of world-wide industries and researchers. In the book “The Third Industrial Revolution,” J. Rifkin has pointed out that the smart grid-centered energy network will facilitate the penetration of renewable energy by taking advantage of multi-energy integration and advanced information technology [1]. In 2015, for example, the Chinese government issued the initiative of “Internet + Smart Energy,”

aiming to promote the synergy of cyber physical systems (CPSs) to improve renewable energy accommodation [2]. In 2016, an energy management platform, developed by LO3 Energy and Consensus, succeeded in a distributed clean energy transaction through the blockchain in Brooklyn, USA. Some other projects, e.g., an E-Energy project in Germany and a smart energy hub in Switzerland [3], are exploring the potential benefits brought on by the energy network.

As a critical technology for energy network transitions, the internet of things (IoT) extends cyber connectivity into physical devices and everyday objects [4]. In the last-meter energy network paradigm, the IoT allows bidirectional communication and two-way interaction to coordinate ubiquitous demand side resources [5]. Recent IEEE Standards, e.g., IEEE 1905.1 [6] and IEEE 802.11ac [7], have provided a foundation for the integration of heterogeneous networking of devices. In the commercial/residential building sector, the U.S. Energy Information Administration (EIA) has predicted a yearly 2% increase of IoT sensors and networks through 2040 [8]. In addition, the IoT can achieve a seamless management of various manufacturing facilities, thus enabling real-time optimization of supply chains and dynamic responses to energy network dispatches [9]. Additionally, the IoT has also been applied in transportation systems to realize inter-vehicular information exchange for smart traffic and parking control [10]. Therefore, the IoT has been advocated as a promising technology to achieve smart energy management and improve the operational efficiency of an energy network.

In the past few years, an increasing penetration of plug-in electric vehicles (PEVs) has further highlighted the importance of using the IoT for energy management. Many recent studies reveal that a large number of uncontrolled PEV fleets can cause power flow and voltage fluctuations, transformer overloading and severe energy losses in distribution networks [11], [12]. However, with the support of the IoT, an aggregation of massive PEVs can hopefully behave as a controllable battery storage system, and effectively respond to dispatch signals due to their fast charging and discharging rates. A wide variety of studies have focused on the IoT-based PEV scheduling in deregulated electricity markets. In [13], a home energy management (HEM) strategy is proposed considering PEV charging in day-ahead markets. The HEM coordinates the PEV charging and users' comfort preferences. In [14], a dynamic programming framework is designed to determine the optimal charging strategy of PEV fleets against the uncertainty in market prices. In [15], a two-stage market bidding model

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for a PEV aggregator formulated with conditional value-at-risk constraints. In [16], a decentralized scheduling method is developed to coordinate PEVs while maintaining data privacy.

Among these references, PEVs are modeled as controllable loads with flexible charging rates. Moreover, some studies introduce vehicle-to-grid (V2G) technology to enable PEVs' discharging. In [17], an IoT-based framework is designed to manage a residential microgrid with V2G systems and renewable energy. In [18], an optimal scheduling model is established to determine the charging and discharging processes of a V2G fleet. To improve the forecast accuracy, an aggregation model is adopted to depict the energy and power boundaries of PEVs. Due to the great flexibility provided by PEVs, some literature has further investigated PEVs' participation in energy and ancillary service markets. In [19], an optimal bidding strategy is developed for an aggregator in day-ahead energy and reserve markets. The objective is to maximize the total profits of a set of PEVs. In [20], an optimization program for a parking lot is proposed to use the available capacities of PEVs to participate in energy and spinning reserve markets. In [21], energy and regulation markets are jointly considered to evaluate the benefits of PEVs providing frequency regulation capacity. In [22], an IoT platform is designed to coordinate PEVs with data centers. With a real-time power control strategy, the aggregation can track the assigned frequency regulation signals. In [23], an optimal bidding framework for V2G fleets is developed to maximize the profits from energy, reserve and regulation markets. A fuzzy optimization method is adopted to model the uncertainties in market prices and renewable generation.

Some researches evaluate the environmental impacts of PEVs in place of traditional gasoline vehicles. Reference [24] points out that the increased popularity of electric vehicles may likely not have a great effect on particulate matter emissions because the emissions from the tire, brake and road wear caused by PEVs are high. In [25], a metric is proposed to quantify the comprehensive environmental impacts of PEVs. In [26], different charging strategies for PEVs are compared in aspects of carbon and pollutant emissions. A case study of California 2030 is conducted. In [27], a life cycle assessment method is adopted to compare the greenhouse gas emissions from an electric vehicle and a gasoline vehicle. Results show that the electricity portfolio can greatly influence the carbon reduction potential of an electric vehicle. In [28], a systematic lifecycle emission comparison is conducted among hybrid, full battery and hydrogen fuel cell electric vehicles.

Most of the existing studies focus on coordinating PEVs with various types of distributed energy resources (DERs) in electricity markets, and evaluate the environmental impacts of PEVs that are substituting for gasoline vehicles. To our best knowledge, however, few studies have investigated the market bidding strategy of PEV and DER aggregation in carbon emission markets. In recent years, many regions across the world have issued policies to incentivize low-carbon energy transitions. China, for example, has launched 7 pilot programs for carbon credit trading since 2014. In practice, a large number of PEVs can be aggregated to charge when renewable power is high, and effectively shift the clean energy to peak

load hours. Thus, the accommodation of renewable energy can be facilitated, which helps reduce carbon and pollutant emissions from fossil fuels. To quantify the double dividends from managing IoT-based PEVs, we conceive a regional energy internet (REI) to bid in joint electricity and carbon trading markets, aggregating a number of DERs, including PEVs, photovoltaic (PV) systems, gas-fired micro-turbines (MTs) and controllable loads. The major contributions are threefold:

1) An optimal bidding framework for a regional energy internet is proposed considering the participation in electricity markets and carbon trading. The REI can trade carbon emission credits (CECs) with a mandatory emission cap imposed. With the support of IoT, REI can aggregate and schedule the V2G-enabled PEV fleets to behave as a controllable storage while coordinating with other DERs. The cases without and with IoT are compared to quantify the economic and environmental benefits of IoT-based PEV management.

2) A two-stage stochastic optimization model is formulated to evaluate the market behavior of REI in joint electricity and carbon markets. The uncertainty of PEVs is characterized by a set of parameters, including arrival/departure time, initial state of charge (SOC) as well as bank capacity. Different charging strategies are compared to evaluate the performance of V2G-enabled schemes.

3) A detailed PEV model is developed, which depicts the relationship between feasible EV power and its SOC during charging/discharging processes. A transformation method is then proposed to determine the feasible region of EV output in the time domain.

Hopefully, the proposed model and method will provide references for distributed energy resources and the regional energy internet to participate in cost-efficient carbon trading.

II. INTERNET OF THINGS PLATFORM

In this paper, an internet of things platform is designed to aggregate the PEV fleets, conventional and renewable energy resources and controllable loads in a regional energy internet to participate in market trading. The schematic of an IoT-based REI is shown in Fig. 1 [29].

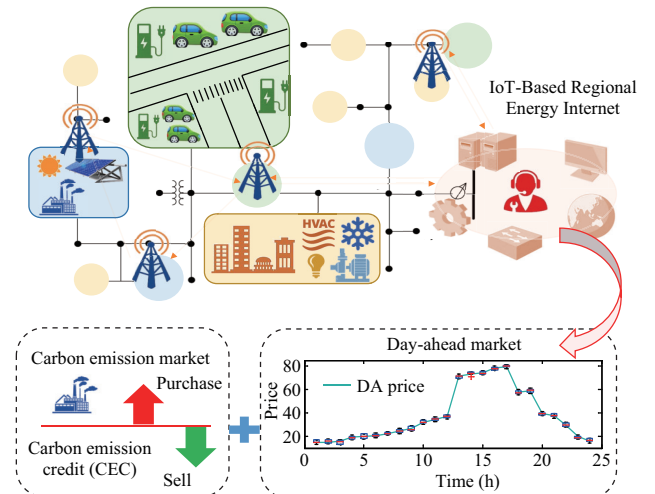


Fig. 1. Schematic of an IoT-based regional energy internet.

In Fig. 1, the IoT technology enables a number of PEVs, PV systems, MTs and controllable loads to communicate and interact with the REI operator. For example, charging stations can directly collect the information regarding PEVs' arrival and departure times as well as the required energy, and send the aggregated information to the operator. The operator then optimally schedules the charging processes of the stations, and sends the dispatch signals back. The IoT technology fully explores the smart interaction capability of demand side resources through wireless communication, e.g., 4G/5G. Therefore, by accessing these devices, the REI operator can take advantage of flexible demand side resources to participate in electricity and carbon markets.

Considering the relatively small capacity, the REI is assumed to act as a price-taker, which submits non-priced (quantity-only) bids [30]. For electricity markets, we consider the REI operator participating in a two-stage market. Given the forecasted day-ahead (DA) and real-time (RT) market prices, the REI operator can submit hourly energy bids in the DA market while anticipating the RT procurements. To depict the uncertainty in RT renewable power, load demand and market prices, a scenario-based stochastic programming is adopted in this paper. A two-settlement mechanism is used for the financial settlement of DA and RT deliveries:

$$R_{s,t}^E = \lambda_t^{DA} P_t^{DA} - \lambda_{s,t}^{RT} (P_t^{DA} - P_{s,t}^{RT}), \quad \forall s, t, \quad (1)$$

where $R_{s,t}^E$ is the REI's revenue from electricity markets; λ_t^{DA} and $\lambda_{s,t}^{RT}$ are the DA and RT market prices; the variable P_t^{DA} is scenario-independent (here-and-now), representing the REI's DA energy bid in time slot t ; and the variable $P_{s,t}^{RT}$ is scenario-related (wait-and-see), representing the REI's RT delivery in scenario s and time slot t .

For carbon trading, a cap-and-trade carbon market is considered in this paper, including CEC allocation, CEC trading and settlement [31]. As shown in Fig. 1, a mandatory cap on the total carbon emissions of the REI is regulated by the government. The REI operator can purchase the CEC inadequacy from the market, and sell the surplus CEC back. In practice, the price volatility in the carbon market is much weaker than that in electricity spot markets. We assume the carbon price as a constant [32], and the settlement mechanism is shown as follows:

$$R_s^C = \lambda^C (E^C - E_s), \quad \forall s, \quad (2)$$

where R_s^C is the REI's revenue from carbon trading; λ^C is the carbon price; E^C is the emission cap of the REI; and the variable E_s represents the REI's daily accumulated carbon emission in scenario s . $E^C - E_s > 0$ indicates that the carbon allowance is sold, and $E^C - E_s < 0$ means the REI purchases the carbon allowance. Note that as the carbon price is constant in DA and RT, there is no need to apply the two-settlement mechanism.

In the traditional case without IoT, PEVs are charged according to users' preferences, which behave as a fixed load rather than a controllable storage. During day hours, the solar power may threaten the security threshold of the REI (e.g., voltage and power flow limits), thus leading to clean energy curtailment. During night time, distributed generation (e.g.,

micro-turbines and gas furnaces) may come online to balance local load and submit market bids, thereby producing carbon emissions. However, IoT allows the PEVs to be aggregated as a storage system, shifting the surplus solar power for the night-time load. As a result, the accommodation of renewable energy can be facilitated, and the market revenues of the REI can be improved.

III. MODEL OF ELECTRIC VEHICLE FLEETS

In this section, a detailed formulation of Li-ion batteries is developed, and the uncertainty of PEVs' behavior is modeled.

A. Electric Vehicle Charging and Discharging Model

For an electric vehicle, the charging process of the Li-ion battery can be divided into two stages: constant current (CC) and constant voltage (CV) [33]. When the state of charge is relatively low, the battery is charging with a constant current and the voltage of the battery cell keeps rising. During this process, the maximum charging power is a constant [34], denoted by $P_{i,\max}^{EV}$, where the subscript " i " indicates the i th EV.

When the battery cell voltage reaches the maximum $V_{i,\max}^{EV}$ at a specific SOC, denoted by SOC_i^C , the charging process will switch to CV in order to protect the battery from degradation. According to the ampere-hour law, the voltage is kept at its maximum and the current decreases exponentially, i.e.,

$$I_{i,t}^{EV} = I_{i,\max}^{EV} e^{-\varepsilon_i t}, \quad \varepsilon_i > 0, \quad (3)$$

where $I_{i,t}^{EV}$ is the current of the i th EV; $I_{i,\max}^{EV}$ is the maximum current; and ε_i is a parameter of the battery cell. Thus, the maximum charging power $P_{i,t,\max}^{EVC}$, is expressed as the product of $V_{i,\max}^{EV}$ and $I_{i,t}^{EV}$, decreasing exponentially during the CV process. It should be noted that the parameter ε_i can be analytically expressed as follows:

$$\varepsilon_i = \frac{\eta_i^{EV} P_{i,\max}^{EV}}{E_{i,\max}^{EV} (1 - SOC_i^C)}, \quad (4)$$

where η_i^{EV} is the efficiency of the i th EV; and $E_{i,\max}^{EV}$ is the capacity of the battery bank. See the Appendix for more details.

During the CV process, the SOC in time slot t , $SOC_{i,t}^{EV}$, is expressed as the integral of charging power:

$$SOC_{i,t}^{EV} = SOC_i^C + \frac{\eta_i^{EV}}{E_{i,\max}^{EV}} \int_0^t P_{i,\tau,\max}^{EVC} d\tau, \quad (5)$$

where the maximum charging power is calculated as the product of $V_{i,\max}^{EV}$ and $I_{i,t}^{EV}$, i.e.,

$$P_{i,t,\max}^{EVC} = V_{i,\max}^{EV} I_{i,t}^{EV} = V_{i,\max}^{EV} I_{i,\max}^{EV} e^{-\varepsilon_i t} = P_{i,\max}^{EV} e^{-\varepsilon_i t}. \quad (6)$$

Substituting (6) to (5), $SOC_{i,t}^{EV}$ is formulated below:

$$SOC_{i,t}^{EV} = SOC_i^C + \frac{\eta_i^{EV}}{\varepsilon_i E_{i,\max}^{EV}} (P_{i,\max}^{EV} - P_{i,t,\max}^{EVC}). \quad (7)$$

Substituting (4) to (7), we can obtain the formulation of the maximum charging power during CV, i.e.,

$$P_{i,t,\max}^{\text{EVC}} = P_{i,\max}^{\text{EV}} \frac{1 - \text{SOC}_{i,t}^{\text{EV}}}{1 - \text{SOC}_i^{\text{C}}}. \quad (8)$$

Therefore, the maximum charging power during the entire charging process is expressed as follows:

$$P_{i,t,\max}^{\text{EVC}} = \begin{cases} P_{i,\max}^{\text{EV}}, & 0 \leq \text{SOC}_{i,t}^{\text{EV}} \leq \text{SOC}_i^{\text{C}}, \\ P_{i,\max}^{\text{EV}} \frac{1 - \text{SOC}_{i,t}^{\text{EV}}}{1 - \text{SOC}_i^{\text{C}}}, & \text{SOC}_i^{\text{C}} < \text{SOC}_{i,t}^{\text{EV}} \leq 1. \end{cases} \quad (9)$$

Similarly, we can obtain the formulation of the maximum discharging power during the discharging process:

$$P_{i,t,\max}^{\text{EVD}} = \begin{cases} P_{i,\max}^{\text{EV}} \frac{\text{SOC}_{i,t}^{\text{EV}}}{\text{SOC}_i^{\text{D}}}, & 0 \leq \text{SOC}_{i,t}^{\text{EV}} \leq \text{SOC}_i^{\text{D}}, \\ P_{i,\max}^{\text{EV}}, & \text{SOC}_i^{\text{D}} < \text{SOC}_{i,t}^{\text{EV}} \leq 1. \end{cases} \quad (10)$$

According to (9) and (10), the feasible region of an EV's output power is illustrated in Fig. 2 [18].

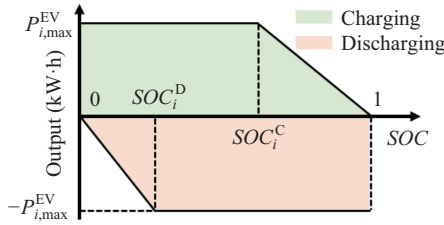


Fig. 2. Illustration of the feasible region of an EV's output power.

B. Charging Station Model

In this paper, a charging station can schedule the charging/discharging processes of PEV fleets to operate as a battery storage. The operational flexibility of a charging station is determined by the available capacity of PEVs. The behavior of each PEV is characterized by a set of parameters, including arrival time (T_i^{arr}), departure time (T_i^{dep}), initial SOC ($\text{SOC}_i^{\text{arr}}$), target SOC ($\text{SOC}_i^{\text{dep}}$) and the feasible region of output power shown in Fig. 2. Therefore, the charging station model is formulated as follows:

$$P_t^{\text{CSC}} = \sum_{i \in \Phi^{\text{EV}}} P_{i,t}^{\text{EVC}}, P_t^{\text{CSD}} = \sum_{i \in \Phi^{\text{EV}}} P_{i,t}^{\text{EVD}}, \quad \forall t, \quad (11)$$

$$P_t^{\text{CSC}}, P_t^{\text{CSD}} \in [0, P_{\max}^{\text{CS}}], \quad \forall t, \quad (12)$$

$$0 \leq P_{i,t}^{\text{EVC}} \leq \alpha_{i,t}^{\text{EV}} P_{i,t,\max}^{\text{EVC}}, \quad \forall i, t, \quad (13)$$

$$0 \leq P_{i,t}^{\text{EVD}} \leq \alpha_{i,t}^{\text{EV}} P_{i,t,\max}^{\text{EVD}}, \quad \forall i, t, \quad (14)$$

$$\text{SOC}_{i,t}^{\text{EV}} = \text{SOC}_{i,t-1}^{\text{EV}} + \frac{1}{E_{i,\max}^{\text{EV}}} (\eta_i^{\text{EV}} P_{i,t-1}^{\text{EVC}} - P_{i,t-1}^{\text{EVD}} / \eta_i^{\text{EV}}), \quad \forall i, t, \quad (15)$$

$$\text{SOC}_{i,T_i^{\text{arr}}}^{\text{EV}} = \text{SOC}_i^{\text{arr}}, \text{SOC}_{i,T_i^{\text{dep}}}^{\text{EV}} \geq \text{SOC}_i^{\text{dep}}, \quad \forall i, \quad (16)$$

$$\text{SOC}_{i,t}^{\text{EV}} \in [0, 1], \quad \forall i, t, \quad (17)$$

where $\Phi^{\text{EV}} = \{1, 2, \dots, N^{\text{EV}}\}$ represents the set of PEVs, where N^{EV} is the PEV number; P_t^{CSC} and P_t^{CSD} are the total charging and discharging power of the charging station; $P_{i,t}^{\text{EVC}}$ and $P_{i,t}^{\text{EVD}}$ are the charging and discharging power of the i th EV; $P_{\max}^{\text{CS}}$ is the capacity of the charging station; $\alpha_{i,t}^{\text{EV}}$ is a parameter indicating the plug-in status of the i th EV, expressed as follows:

$$\alpha_{i,t}^{\text{EV}} = \begin{cases} 0, & t < T_i^{\text{arr}} \text{ or } t > T_i^{\text{dep}}, \\ 1, & T_i^{\text{arr}} \leq t \leq T_i^{\text{dep}}. \end{cases} \quad (18)$$

In (11), the power of the charging station is the aggregation of PEV fleets. (12) shows the capacity of the charging station. In constraints (13) and (14), the charging and discharging power of an EV are restricted by its maximum power, as shown in (9) and (10). In (15), the SOC of an EV is related to the charging and discharging energy during a time slot. In constraint (16), the initial SOC is set to the SOC of an EV in arrival time, and the SOC in departure time must be greater than the target. Note that we assume the SOC of each EV can vary from 0 to 1 as shown in (17). This assumption can be readily relaxed by modifying the ranges in (9) and (10).

C. Feasible Region Transformation

As shown in Fig. 2, the maximum charging power in constraints (13) is related to an EV's SOC. To transform the feasible EV power in the time domain, we introduce two auxiliary binary variables $\beta_{i,t,\text{CC}}^{\text{EVC}}$ and $\beta_{i,t,\text{CV}}^{\text{EVC}}$ to represent the status of CC and CV charging stages: $\beta_{i,t,\text{CC}}^{\text{EVC}} = 1$ and $\beta_{i,t,\text{CV}}^{\text{EVC}} = 0$ indicates the CC charging stage of an EV, and $\beta_{i,t,\text{CC}}^{\text{EVC}} = 0$ and $\beta_{i,t,\text{CV}}^{\text{EVC}} = 1$ indicates the CV charging stage of an EV. Therefore, constraint (13) can be replaced by the following:

$$\beta_{i,t,\text{CC}}^{\text{EVC}} + \beta_{i,t,\text{CV}}^{\text{EVC}} = 1, \quad \forall i, t, \quad (19)$$

$$0 \leq \text{SOC}_{i,t,\text{CC}}^{\text{EV}} \leq \text{SOC}_i^{\text{C}} \cdot \beta_{i,t,\text{CC}}^{\text{EVC}}, \quad \forall i, t, \quad (20)$$

$$\text{SOC}_i^{\text{C}} \cdot \beta_{i,t,\text{CV}}^{\text{EVC}} \leq \text{SOC}_{i,t,\text{CV}}^{\text{EV}} \leq \beta_{i,t,\text{CV}}^{\text{EVC}}, \quad \forall i, t, \quad (21)$$

$$\text{SOC}_{i,t}^{\text{EV}} = \text{SOC}_{i,t,\text{CC}}^{\text{EV}} + \text{SOC}_{i,t,\text{CV}}^{\text{EV}}, \quad \forall i, t, \quad (22)$$

$$0 \leq P_{i,t}^{\text{EVC}} \leq \alpha_{i,t}^{\text{EV}} P_{i,t,\max}^{\text{EVC}}, \quad \forall i, t, \quad (23)$$

$$0 \leq P_{i,t}^{\text{EVC}} \leq \alpha_{i,t}^{\text{EV}} P_{i,\max}^{\text{EV}} \frac{1 - \text{SOC}_{i,t}^{\text{EV}}}{1 - \text{SOC}_i^{\text{C}}}, \quad \forall i, t, \quad (24)$$

where $\text{SOC}_{i,t,\text{CC}}^{\text{EV}}$ and $\text{SOC}_{i,t,\text{CV}}^{\text{EV}}$ represent the SOC in the CC and CV stages, respectively. By this means, the charging power can be restricted in the two intervals, respectively. Similarly, constraint (14) can be replaced by the following:

$$\beta_{i,t,\text{CC}}^{\text{EVD}} + \beta_{i,t,\text{CV}}^{\text{EVD}} = 1, \quad \forall i, t, \quad (25)$$

$$0 \leq \text{SOC}_{i,t,\text{CC}}^{\text{EV}} \leq \text{SOC}_i^{\text{D}} \cdot \beta_{i,t,\text{CC}}^{\text{EVD}}, \quad \forall i, t, \quad (26)$$

$$\text{SOC}_i^{\text{D}} \cdot \beta_{i,t,\text{CV}}^{\text{EVD}} \leq \text{SOC}_{i,t,\text{CV}}^{\text{EV}} \leq \beta_{i,t,\text{CV}}^{\text{EVD}}, \quad \forall i, t, \quad (27)$$

$$0 \leq P_{i,t}^{\text{EVD}} \leq \alpha_{i,t}^{\text{EV}} P_{i,t,\max}^{\text{EVD}}, \quad \forall i, t, \quad (28)$$

$$0 \leq P_{i,t}^{\text{EVD}} \leq \alpha_{i,t}^{\text{EV}} P_{i,\max}^{\text{EV}} \frac{\text{SOC}_{i,t}^{\text{EV}}}{\text{SOC}_i^{\text{D}}}, \quad \forall i, t, \quad (29)$$

D. Uncertainty Modeling

In practice, a REI operator has to factor a number of uncertainties into the DA scheduling for PEV fleets. These

uncertainties come from the stochastic behaviors of individual EV drivers. To model the uncertainties of PEVs, we assume that the initial SOC, the arrival time and the departure time of PEVs obey truncated Gaussian distributions, which has been widely adopted in existing literature [35], [36]. The probability distribution functions (PDFs) of the stochastic variables are shown in Fig. 3, and the parameters are shown in Table I. Note that for each EV, the arrival time should not exceed the departure time.

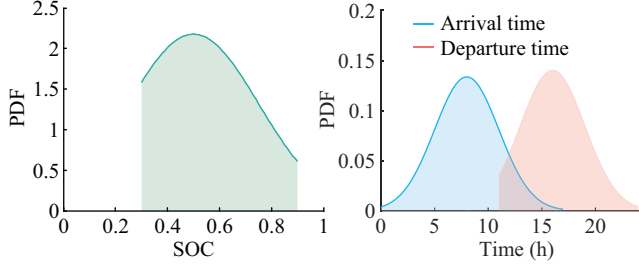


Fig. 3. Probability distribution functions of the stochastic variables.

TABLE I
PARAMETERS OF THE STOCHASTIC VARIABLES

Variable	Mean	Standard deviation	Min	Max
Initial SOC	0.5	0.25	0.3	0.9
Arrival time	8 h	3 h	0 h	17 h
Departure time	16 h	3 h	11 h	24 h

In this paper, a scenario-based stochastic programming is employed to depict the various sources of uncertainties [37], including PEVs, RT market prices, solar power and electric load. The scenarios of PEVs are generated from the aforementioned PDFs, and the scenarios of other stochastic variables can be extracted from realistic datasets. Let $\Phi^S = \{1, 2, \dots, N^S\}$ represent the set of the scenarios, where N^S is the scenario number. The probability of scenario s is denoted by γ_s .

In practice, the capacity of the PEVs, i.e., $E_{i,\max}^{\text{EV}}$, may not be the same. As shown in Fig. 4, a distribution of EV battery capacities is collected from [38], and adopted in this paper.

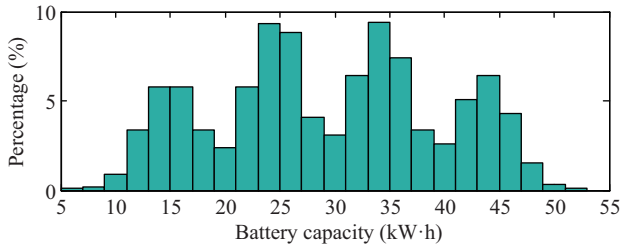


Fig. 4. Distribution of 24 classes of EV battery capacities.

IV. MODEL OF OPTIMAL MARKET BIDDING

In this section, an optimal market bidding model of a regional energy internet is proposed considering its participation in electricity and carbon markets.

A. Bidding Model

The problem of the optimal bidding strategy is formulated as

a two-stage stochastic linear programming model as follows:

$$\begin{aligned} \max_{X^{\text{DA}}, X^{\text{RT}}} & \sum_{s \in \Phi^S} \sum_{t \in \Phi^T} \gamma_s R_{s,t}^E + \sum_{s \in \Phi^S} \gamma_s R_s^C \\ & - \sum_{s \in \Phi^S} \sum_{t \in \Phi^T} \sum_{i \in \Phi^{\text{MT}}} \gamma_s c_i P_{i,s,t}^{\text{MT,RT}} \end{aligned} \quad (30)$$

s.t.

$$\begin{aligned} P_t^{\text{DA}} = & \sum_{i \in \Phi^{\text{MT}}} P_{i,t}^{\text{MT,DA}} + \sum_{i \in \Phi^{\text{PV}}} P_{i,t}^{\text{PV,DA}} \\ & + P_t^{\text{CSD,DA}} - P_t^{\text{CSC,DA}} - P_t^{\text{L,DA}}, \quad \forall t, \end{aligned} \quad (31)$$

$$P_{s,t}^{\text{RT}} = \sum_{i \in \Phi^{\text{MT}}} P_{i,s,t}^{\text{MT,RT}} + \sum_{i \in \Phi^{\text{PV}}} P_{i,s,t}^{\text{PV,RT}} \quad (32)$$

$$P_t^{\text{DA}} = +P_t^{\text{CSD,RT}} - P_t^{\text{CSC,RT}} - P_t^{\text{L,RT}}, \quad \forall s, t, \quad (33)$$

$$P_t^{\text{DA}}, P_{s,t}^{\text{RT}} \in [-P_{\max}^{\text{REI}}, P_{\max}^{\text{REI}}], \quad \forall s, t, \quad (34)$$

$$E_s = \sum_{t \in \Phi^T} \sum_{i \in \Phi^{\text{MT}}} e_i P_{i,s,t}^{\text{MT,RT}}, \quad \forall s, \quad (35)$$

$$\begin{aligned} -\delta_i^{\text{ADJ}} P_{i,\max}^{\text{MT}} & \leq P_{i,t}^{\text{MT,DA}} - P_{i,s,t}^{\text{MT,RT}} \\ & \leq \delta_i^{\text{ADJ}} P_{i,\max}^{\text{MT}}, \quad \forall i, s, t, \end{aligned} \quad (36)$$

$$P_{i,t}^{\text{MT,DA}}, P_{i,s,t}^{\text{MT,RT}} \in [0, P_{i,\max}^{\text{MT}}], \quad \forall i, s, t, \quad (37)$$

$$\begin{aligned} P_{i,t}^{\text{PV,DA}} & \in [0, P_{i,t}^{\text{PVF,DA}}], P_{i,s,t}^{\text{PV,RT}} \\ & \in [0, P_{i,s,t}^{\text{PVF,RT}}], \quad \forall i, s, t, \end{aligned} \quad (38)$$

$$\sum_{t \in \Phi^T} P_t^{\text{L,DA}} \geq E_{\min}^{\text{L}}, \quad (39)$$

$$\sum_{t \in \Phi^T} P_{s,t}^{\text{L,RT}} \geq E_{s,\min}^{\text{L}}, \quad \forall s, \quad (40)$$

$$\begin{aligned} P_t^{\text{L,DA}} & \in [P_{t,\min}^{\text{L,DA}}, P_{t,\max}^{\text{L,DA}}], P_{s,t}^{\text{L,RT}} \\ & \in [P_{s,t,\min}^{\text{L,RT}}, P_{s,t,\max}^{\text{L,RT}}], \quad \forall s, t, \end{aligned} \quad (40)$$

constraints (11)–(18) for DA and RT, where the decision variables are denoted by X^{DA} and X^{RT} , representing the DA- and RT-related variables, respectively, including REI's DA energy bids P_t^{DA} , the power of the i th MT $P_{i,t}^{\text{MT,DA}}$, the power of the i th PV $P_{i,t}^{\text{PV,DA}}$, the charging/discharging power of the station $P_t^{\text{CSD,DA}}/P_t^{\text{CSC,DA}}$, the load $P_t^{\text{L,DA}}$, and the associated variables with the superscript "RT"; Φ^T , Φ^{MT} and Φ^{PV} are the sets of time slots, micro-turbines and photovoltaic systems, respectively; $P_{\max}^{\text{REI}}$ is the capacity of the REI, indicating the capacity of a substation or a distribution grid; c_i and e_i are the cost and carbon emission rate of the i th MT; $P_{i,\max}^{\text{MT}}$ is the capacity of the i th MT; δ_i^{ADJ} is the limit for the RT adjustment power of the i th MT; $P_{i,t}^{\text{PVF,DA}}$ and $P_{i,s,t}^{\text{PVF,RT}}$ are the DA forecasted power and RT scenario-related forecast, respectively; $E_{\min}^{\text{L}}$ and $E_{s,\min}^{\text{L}}$ are the DA forecasted daily load requirement and RT forecast, respectively; $P_{t,\min}^{\text{L,DA}}$, $P_{t,\max}^{\text{L,DA}}$, $P_{s,t,\min}^{\text{L,RT}}$ and $P_{s,t,\max}^{\text{L,RT}}$ are the DA and RT minimum and maximum load, respectively.

The objective of the bidding strategy is to maximize the DA profits anticipating the RT adjustments. In (30), the first term is the profits from DA and RT markets, the second term is the profits from carbon trading and the third term is the generation costs of MTs. In (31) and (32), the energy bids of the REI

equal the power from MTs, PVs and PEVs minus electric load. In (33), the bidding of the REI is restricted by its capacity. (34) shows the carbon emissions are released from MTs. In (35), the RT adjustments of MTs are bounded. Constraints (36), (37) and (40) show the lower and upper limits of MTs, PVs and load. Constraints (38) and (39) show the minimum requirement for daily load. Note that the constraints for the charging station (11)–(18) are extended to DA and RT forms.

B. Benefits of IoT

The potential benefits of IoT are analyzed in Fig. 5.

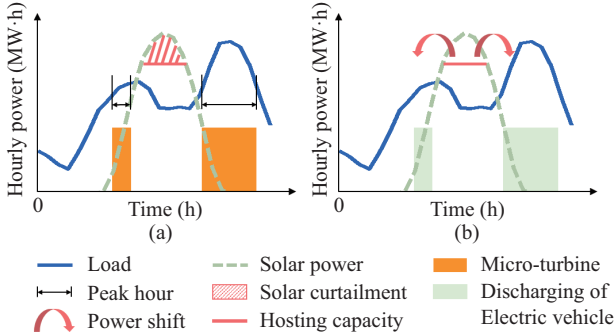


Fig. 5. Benefit analysis brought on by the IoT technology.

Figure 5 (a) illustrates the traditional case without IoT, in which PEVs behave as a fixed load rather than as controllable energy storage. During peak hours, gas-fired MTs have to start up for load balance, thus yielding carbon emissions. However, when solar power is extremely high at noon, the REI may not have sufficient hosting capacity to accommodate all the solar power, and some clean energy has to be curtailed.

In Fig. 5 (b), an illustration for the IoT-enabled operation is provided, in which PEVs are aggregated and managed as a battery storage. In practice, a number of PEVs can work in a relatively flexible range while satisfying the required SOC at departure time. Hence, PEVs can absorb the surplus solar energy at noon, improving the energy efficiency of the REI. On the other hand, PEVs can discharge during peak hours in place of MTs, which significantly reduces the carbon emissions. With the help of the IoT, the accommodation of renewable energy can be facilitated toward beneficial market bidding, thus achieving Pareto Improvement.

V. CASE STUDIES

Case studies are performed using MATLAB R2013b and CPLEX 12.4 [39] on a computer with 2.40 GHz CPU and 8 GB RAM. A regional energy internet with 50 electric vehicles, 10 PV systems and 5 MTs is selected as the base case.

A. Data Description

To depict the uncertainty in PEVs, solar power, load and electricity market prices, 10 scenarios are generated from the yearly data and probability distributions. The battery capacity of each EVs derived from the distribution in Fig. 3, shown in Table II.

TABLE II
BATTERY CAPACITY OF 50 ELECTRIC VEHICLES

Capacity (kW·h)	15	20	25	30	35	40	45
Number	8	6	10	6	10	4	6

In this paper, the electricity market prices are collected from the PJM market [40]. The solar power data are collected from [41]. Fig. 6 shows the electricity market price and total solar power data.

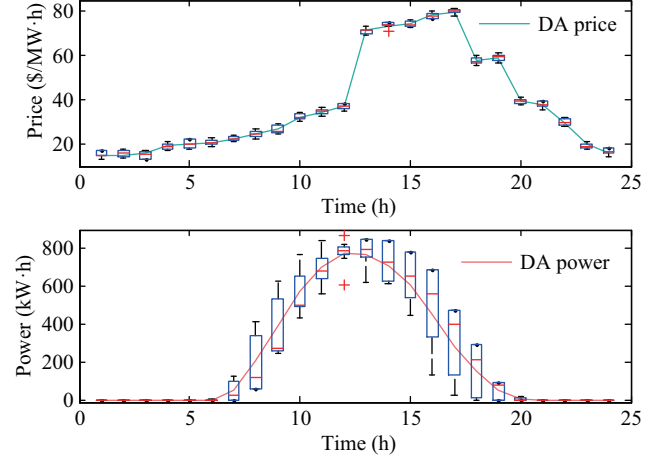


Fig. 6. Electricity market price and total solar power data.

The price of carbon emission credits is set to 12.3 \$/ton [31], and the daily carbon emission cap is set to 125.0 kg. The charging/discharging efficiency of PEVs is 95%, and the maximal power of an EV is 5 kW. Electric load data are collected from the PJM market [42], and the hourly adjustment range is set to 0.9 and 1.1 times that of the original data. The maximum bidding capacity of the REI is 250 kW. The parameters of MTs are shown in Table III. The RT adjustment limit of MTs is 10%.

TABLE III
PARAMETERS OF 5 GAS-FIRED MICRO-TURBINES

No.	Capacity (kW)	Cost (\$/ (kW·h))	Emission rate (kg/ (kW·h))
1	50	0.055	0.76
2	50	0.065	0.90
3	50	0.075	1.04
4	50	0.085	1.18
5	50	0.095	1.32

To demonstrate the effectiveness and benefits of the proposed framework, three methods are compared in the case studies: 1) M1, which is the proposed framework with V2G-enabled controllable PEV fleets; 2) M2, in which V2G is not available but PEV fleets can be controlled to change the charging rates; and 3) M3, which is the traditional case without IoT, indicating that PEV fleets are charged at the maximum rate as soon as they arrive.

B. Optimal Bidding Strategy

The DA optimal bidding strategies of the REI and PEVs are shown in Fig. 7 and Fig. 8.

In Fig. 7, the REI can bid more surplus power in M1 than in M2 and M3, especially during peak hours from 8:00 to 11:00.

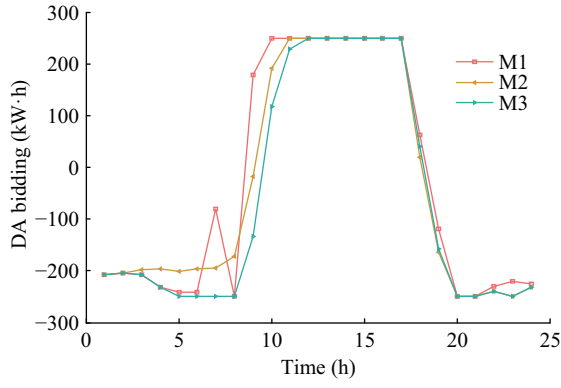


Fig. 7. DA optimal bidding strategies of the REI.

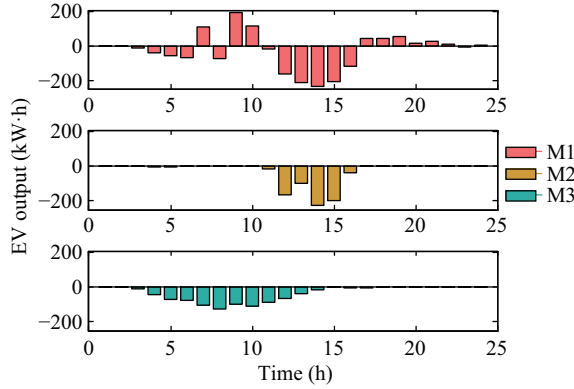


Fig. 8. DA optimal bidding strategies of the PEVs.

This is because the PEVs can flexibly charge and discharge in M1. As shown in Fig. 8, the y -axis represents the difference of the discharge and charge power. In M1, the PEVs charge from 3:00 to 6:00 when market prices are low, or from 11:00 to 16:00 when solar power is high. During peak hours from 9:00 to 10:00 and from 17:00 to 21:00, the PEVs discharge in order to satisfy electric load in place of MTs. In M2, the PEVs can only adjust the charging rates, and thus charge at noon to accommodate the surplus solar power. In M3, however, the PEVs are charged according to users' preferences, i.e., at the maximum charging rate after arrival. Hence, without the energy management brought on by the IoT, a large number of the PEVs are charged during peak hours. The solar power and carbon emissions are shown in Fig. 9.

From the results, with the help of V2G, the REI can accommodate more solar power in M1 than in M2 and M3. The total amounts of daily solar energy in the three methods are 5.74, 5.52 and 5.09 MW·h, respectively. Hence, the solar power accommodation in M1 can be improved by 3.99% and 12.77% compared with those in M2 and M3, respectively. Since more clean energy can be integrated, the daily carbon emissions in M1 are much less than those in M2 and M3. The daily carbon emissions in the three methods are 46.76, 123.72 and 171.98 kg, respectively. Thus, with the emission cap equaling 125 kg, the REI in M1 and M2 can earn profits by selling CECs, while the REI in M3 has to purchase an extra 46.98 kg CECs from the carbon market.

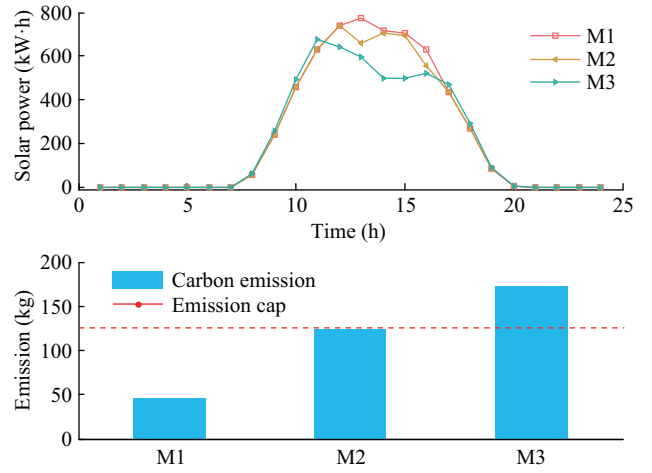


Fig. 9. Comparisons of solar power accommodation and carbon emissions.

C. Market Revenue

The market revenues of the three methods are compared in Table IV.

TABLE IV
MARKET REVENUES OF THE THREE METHODS

Revenue/Method	M1	M2	M3
DA	\$ 55.86	\$ 44.49	\$ 33.67
RT	\$ 7.96	\$ -13.92	\$ -7.03
Carbon	\$ 0.96	\$ 0.02	\$ -0.58
Total	\$ 64.78	\$ 30.59	\$ 26.06

As compared in Table IV, the REI in M1 can significantly increase its market revenues compared with those in M2 and M3. In the DA markets, since more solar energy can be accommodated, M1 can improve the DA revenues by 25.56% and 65.90% compared with M2 and M3, respectively. In the RT markets, taking advantage of the V2G-enable PEVs, the REI can earn profits in M1, but pay for the adjustment costs in M2 and M3. Additionally, the expected generations from MTs in M1, M2 and M3 are 61.52, 160.86 and 224.35 kW·h, producing 46.76, 123.72 and 171.98 kg carbon, respectively. Hence, M1 can achieve the highest carbon revenues among the three methods.

D. Impact of PEV Numbers

In this subsection, we conduct sensitivity analysis on the impact of the number of electric vehicles, which may greatly influence the available storage capacity. Fig. 10 shows the market revenues in M1 with the increase in the number of PEVs. Fig. 11 shows the daily solar energy accommodation in M1 with the increase in the number of PEVs.

As can be seen, with the number of PEVs varying from 10 to 100, the total market revenues greatly increase from \$ 36.07 to \$ 86.96. When there are fewer PEVs in the charging station, the aggregated storage capacity is lower, which shifts less solar energy to peak hours. As a result, compared with the case with 10 PEVs, the daily solar energy accommodation can be improved by 16.33% in the case with 100 PEVs. With more clean energy consumed, the REI can earn higher revenues from carbon trading. In the case with 100 PEVs, the revenue from

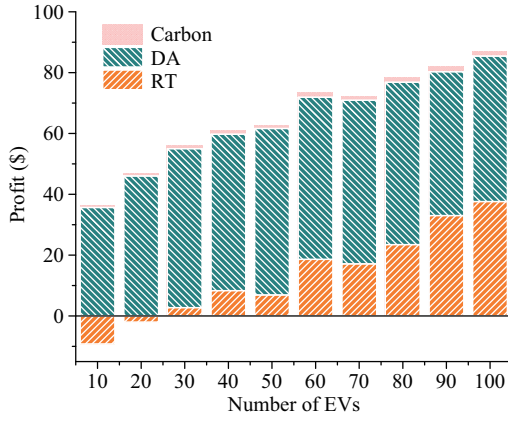


Fig. 10. Market revenues in M1 with the increase in the number of PEVs.

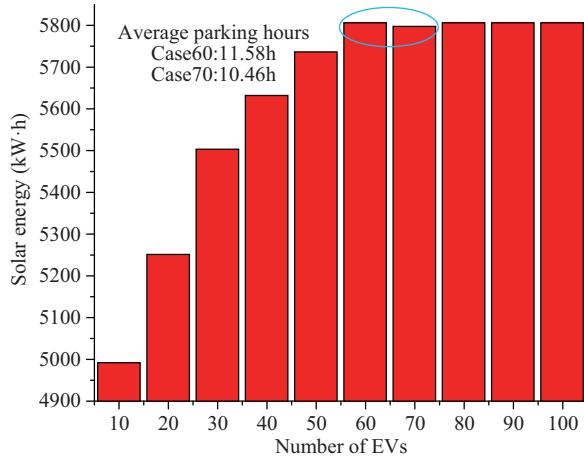


Fig. 11. Daily solar energy accommodation in M1 with the increase in the number of PEVs.

carbon trading is \$ 1.52, but the value in the case with 10 PEVs is only \$ 0.42.

Another significant impact is the increase in RT market revenues. A large number of PEVs can greatly improve the fast responsive capability of the REI in RT markets. In the case with 10 PEVs, the RT adjustment cost is \$ 9.26. However, in the case with 100 PEVs, the revenue from RT markets reaches \$ 37.63.

It should be noted that the market revenues and the solar energy accommodation in the case with 60 PEVs are even higher than those with 70 PEVs. In the case with 60 PEVs, the total market revenue and solar energy are \$ 73.44 and 5803.47 kW·h, respectively. However, in the case with 70 PEVs, the values are \$ 72.27 and 5795.16 kW·h, respectively. This is because the average parking hour in the case with 60 PEVs is longer than that with 70 PEVs. As can be seen in Fig. 11, the average parking hour in the 60 PEV case reaches 11.58 h, and the value in the 70 PEV case is 10.46 h. A longer parking hour indicates a larger available storage capacity over the daily time horizon. Thus, a larger number of PEVs do not necessarily indicate more available storage capacity and a higher level of market revenues. The arrival time, the departure time and the initial SOC of the PEVs all have an impact on the above two aspects.

E. Impacts of Battery Degradation

In this subsection, we evaluate the impacts of battery degradation on the charging/discharging behavior of EVs. A degradation cost term is added in the objective function (30), shown as follows:

$$\begin{aligned} \max_{X^{DA}, X^{RT}} & \sum_{s \in \Phi^S} \sum_{t \in \Phi^T} \gamma_s R_{s,t}^E + \sum_{s \in \Phi^S} \gamma_s R_s^C \quad (41) \\ & - \sum_{s \in \Phi^S} \sum_{t \in \Phi^T} \sum_{i \in \Phi^{MT}} \gamma_s c_i P_{i,s,t}^{MT,RT} \\ & - \sum_{s \in \Phi^S} \sum_{t \in \Phi^T} \sum_{i \in \Phi^{EV}} \gamma_s \delta_i^{EV} P_{i,s,t}^{EVD}, \end{aligned}$$

where the last term represents the degradation cost of EVs; δ_i^{EV} denotes the battery degradation cost for the V2G process, measured in \$/kWh. With the increase in battery degradation cost, the daily discharging power of V2G-enabled EVs during market bidding is shown in Fig. 12.

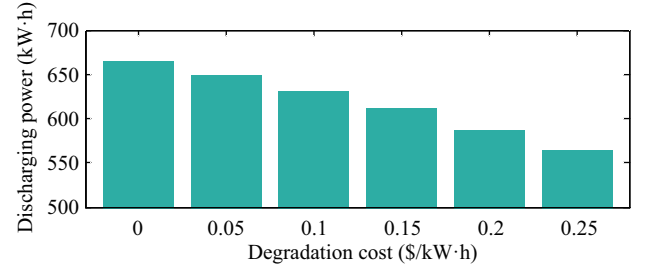


Fig. 12. Daily discharging power of V2G-enabled EVs during market bidding.

When the degradation cost varies from 0 to 0.25 \$/kW·h, the discharging power of V2G-enabled EVs greatly decreases by 15.07%, from 664.97 to 564.76 kW·h. A higher degradation cost indicates that the deployment of V2G is more costly, and thus the REI operator will dispatch less discharging power from the EVs.

VI. CONCLUSION

In this paper, an optimal bidding framework for a V2G-enabled regional energy internet is proposed considering the participation in electricity and carbon trading markets. An IoT platform is designed, in which the REI operator manages a number of DERs, including the PEVs in a charging station, the distributed PV systems, gas-fired MTs and controllable load. A detailed model for electric vehicles is formulated to depict the charging and discharging capability. In the case studies, real-world datasets are adopted, and three methods are compared, which demonstrates that: 1) Compared with the cases without IoT or V2G, the proposed IoT-based bidding framework can flexibly schedule the charging and discharging processes of PEV fleets, thus effectively facilitating the accommodation of renewable energy. 2) By means of the proposed bidding method, the REI can significantly improve the market revenues while reducing the carbon emissions, yielding both economic and environmental benefits. 3) Generally speaking, with the increase in the number of PEVs in the charging station, the IoT-based platform can aggregate more available storage

capacity, and help the REI to earn more market revenues. However, the total amount of available storage capacity is jointly determined by some stochastic variables, e.g., the parking hours and the initial SOC. Hence, a larger number of PEVs do not necessarily indicate a higher level of market revenues.

Three issues need further investigation in the future: 1) With an increasing integration of electric vehicles in power grids, the market operation and marginal prices will be greatly influenced. It deserves an in-depth study to investigate the market equilibrium of multiple REIs in wholesale markets and carbon trading. 2) A large number of PEV fleets can be aggregated not only for profitable market bidding, but also to address other issues, e.g., voltage excursion, thermal overloading, distribution grid resilience, etc. The grid- and environment-friendly impacts brought on by the IoT-based PEVs need a systematic study. 3) In practice, it is hardly possible to efficiently solve an optimal scheduling program with massive PEVs, say 10,000. Due to the computation burden and data privacy, an efficient decomposition solution algorithm should be put forward.

APPENDIX

In this Appendix, the analytical expression for the parameter of an electric vehicle ε_i is deduced. As demonstrated in Section III. A, the charging process for an electric vehicle can be divided into CC and CV stages. During the CC stage, the battery is charged at its maximum charging power $P_{i,\max}^{\text{EV}}$ until the SOC reaches a specific point, i.e., SOC_i^{C} . Then the charging mode is switched to CV. During the CV stage, the SOC of the battery is expressed as follows:

$$\begin{aligned} \text{SOC}_{i,t}^{\text{EV}} &= \text{SOC}_i^{\text{C}} + \frac{\eta_i^{\text{EV}}}{E_{i,\max}^{\text{EV}}} \int_0^t P_{i,\tau,\max}^{\text{EVC}} d\tau \\ &= \text{SOC}_i^{\text{C}} + \frac{\eta_i^{\text{EV}} P_{i,\max}^{\text{EV}}}{E_{i,\max}^{\text{EV}}} \int_0^t e^{-\varepsilon_i \tau} d\tau \\ &= \text{SOC}_i^{\text{C}} + \frac{\eta_i^{\text{EV}} P_{i,\max}^{\text{EV}}}{E_{i,\max}^{\text{EV}} \varepsilon_i} (1 - e^{-\varepsilon_i t}). \end{aligned} \quad (42)$$

Note that when $t \rightarrow +\infty$, $\text{SOC}_{i,t}^{\text{EV}} \rightarrow 1$. Thus, we can derive the following expression:

$$1 = \text{SOC}_i^{\text{C}} + \frac{\eta_i^{\text{EV}} P_{i,\max}^{\text{EV}}}{E_{i,\max}^{\text{EV}} \varepsilon_i} \Rightarrow \varepsilon_i = \frac{\eta_i^{\text{EV}} P_{i,\max}^{\text{EV}}}{E_{i,\max}^{\text{EV}} (1 - \text{SOC}_i^{\text{C}})}. \quad (43)$$

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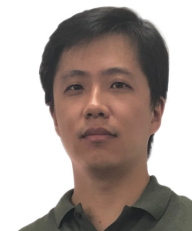
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