Optimal bidding strategy for virtual power plants considering the feasible region of vehicle-to-grid

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Abstract
With the rapid development of vehicle-to-grid (V2G) technology, the use of the internet of things and advanced information technology to achieve the optimal dispatch of large-scale plug-in electric vehicles (PEVs) has become an important focus of scientific research and engineering practice worldwide. In order to achieve a balance between mass distributed energy resources and the secure and economic operation of the power grid, the authors propose an optimal market bidding strategy for a virtual power plant considering the feasible region of V2G. A detailed battery model considering the V2G mode of PEVs is established. A two-stage stochastic optimisation model for the virtual power plant considering massive volumes of PEVs is built, taking into account the day-ahead market revenue and the costs brought about by real-time market deviations. Three bidding strategies—PEVs charging immediately after arrival, without V2G, and considering V2G—are compared using case studies to demonstrate the efficiency and effectiveness of the proposed strategy. Through the complete interaction between PEVs and the virtual power plant, this V2G-based strategy can coordinate distributed energy resources, promote the accommodation of renewable energy, and significantly improve the economy of the virtual power plant operation.

1 | INTRODUCTION

Owing to their characteristics of reliability, flexibility, economy, and environmental friendliness, distributed energy resources (DERs) are gradually being employed in power systems in several countries to deal with energy shortages and environmental issues. However, the uncertainty and intermittence inherent in distributed generation pose challenges to the security and stability of the power system [1]. In addition, the distributed grid-connection construction of DERs is a high-cost process, whereas a centralised grid-connection is in direct conflict with the concept of distributed development. In order to achieve a balance between the massive promotion of DERs and the secure and economic operation of the power grid, Shimon Awerbuch proposed the concept of a virtual power plant (VPP) for the first time in 1997 [2]. As a cluster that aggregates DERs, flexible loads, and energy storage systems, the VPP participates in the grid operation in the form of a special power plant.

Numerous studies have been conducted by domestic and foreign scholars in relation to the economic operation and management of a VPP. The authors in [3] proposed the bidding strategy of a VPP participating in a joint energy and reserve market. In conjunction with the wholesale and retail markets, a comprehensive energy planning scheme for distributed generation was proposed based on energy sharing [4]. In another study [5], the VPP was authorised as a flexible coordinator of wind farms and coal-fired plants in the vicinity, and the price proposed by the grid corporation to VPPs served as an incentive to coordinate the generation of output. A suitable schedule of interactions and communications between all components of the VPP related to the electricity market participation and network operation was presented in a sequence diagram in [6]. By employing the latest forecasts through a rolling horizon approach and rescheduling flexibly, the VPP can reduce the uncertainty associated with the input data and restrain undesirable curtailments. Considering the uncertainty of the market price, the optimal investment strategy of DERs was studied and an analysis of the maximum economic revenues of a VPP was conducted in [7]. The authors in [8] focused on the comprehensive energy planning of photovoltaic (PV) power and energy storage, and analysed the
power supply reliability of DERs along with the economy of the VPP.

In recent years, with the increasing popularity of plug-in electric vehicles (PEVs), PEVs have been increasingly integrated at the level of system operation and market bidding, and their advantage in terms of flexibility has become increasingly prominent in the operation and management of VPPs. Traditionally, in the absence of charging and discharging regulations, a large number of uncontrolled PEVs would cause problems such as fluctuations in the power flow and voltage in the distribution network, loss of energy, and the overloading of transformers [9]. With the regulation of information technology in VPPs, the PEV fleet is expected to be aggregated into a controllable virtual energy storage system, and to effectively respond to dispatch instructions for fast charging. A dynamic planning framework was designed in [10,11] to determine the optimal charging strategy for a PEV fleet under conditions of uncertain market prices.

The application of the vehicle-to-grid (V2G) technology involves a bidirectional interaction between PEVs and the power grid, thus realizing the discharge of electrical energy from PEVs to the power grid. Therefore, PEVs supporting the V2G technology can be modelled as mobile energy storage devices with flexible charging and discharging rates. Considering the bidirectional flow of electrical energy, the charging and discharging control strategy of a PEV fleet was studied in [12]. To improve the prediction accuracy, an optimal scheduling model established in [13] used an aggregation model to describe the energy and power boundaries of electric vehicles. The authors in [14] proposed an optimal bidding model for V2G fleets to maximize the revenues of DERs and energy storage devices considering the regulatory market. The charging and discharging schedules of PEVs were designed based on the day-ahead market data [15–17] without considering forecast deviations in real time, which cause discrepancies between the day-ahead market and the real-time market [18]. Moreover, taking into account the bidirectional interaction between PEVs and the power grid, reasonable optimal scheduling strategies for the regional operation of PEVs were proposed. However, an efficient and accurate feasible region for electric vehicle dispatch was not formulated in [15–17]. In [19,20], the aggregate controllable energy and power boundaries of a V2G fleet were established; however, the actual charging and discharging characteristics of the PEV battery were not taken into consideration. A model of the relationship between the battery charging/discharging power and the state of charge is worth exploring.

In the existing literature, many studies have focused on the application of PEVs as distributed energy storage to improve the operational flexibility of the power grid. However, there are few studies exploring the role and value of PEVs in enabling VPPs to participate in the electricity spot market. With the rapid development of PEVs, a large number of them will be connected to the active distribution network, microgrids, and VPPs in the future, which will enable full exploitation of their flexible adjustment ability as controllable energy storage, and will enhance the competitiveness of VPPs in the electricity market. Furthermore, based on the charging/discharging characteristics of the PEV battery, the relationship between the battery charging/discharging power and state of charge can be determined, which will enhance the accuracy of the V2G dispatching feasible region and improve the profits of VPPs participating in the electricity market.

Based on the above research considerations, a bidding strategy for VPPs in the electricity market taking into account the V2G mode was designed. The innovations and contributions of this study are threefold:

(i) An optimal market bidding framework for VPPs is proposed that takes into consideration the V2G mode of PEVs. The impact of V2G technology on market bidding for a VPP was analysed in detail, and based on the case analysis, an annual simulation with various strategies was conducted.

(ii) Based on the flexible adjustment of the charging and discharging rates of PEVs, a detailed model of PEVs supporting the V2G technology was formulated. The V2G dispatching feasible region in the VPP operation was presented to describe the battery charging and discharging characteristics, and the controllable charging and discharging power boundaries of PEVs were determined.

(iii) A two-stage stochastic optimisation model in the day-ahead and real-time markets was established to determine the schedule of PEVs and DERs. The stochastic programming method based on multiple scenarios was applied to optimise the operation simulation of VPPs participating in the spot market. The randomness and fluctuation of PEVs, market prices, PV output, and load demand were incorporated into the optimisation model to achieve the optimal bidding.

2 | OPERATION MECHANISM OF THE VPP

The VPP integrates various kinds of DERs in the region and adopts advanced information technology to aggregate power generation systems, energy storage devices, and flexible loads into a virtual controllable aggregator. The VPP offers opportunities of direct market participation to diverse resources as subscribers. Therefore, the VPP can tap the application potential of DERs, coordinate the interaction between DERs and the power grid, and realize the real-time optimisation of the supply chain and intelligent management of the power system.

A VPP considering the V2G mode was designed, which integrates PEVs, conventional energy, renewable energy, and flexible loads to participate in the two-stage market of energy trading. Its operation mechanism is illustrated in Figure 1.

The VPP integrates multiple elements such as physical resources, an information system, and an evaluation system. It transmits physical data to the evaluation system through information technology, where considering economic value as the driving force of operation [21], the efficient optimisation and integration of various flexible resources are realised. As shown in Figure 1, the information system of the VPP can realize the communication and interaction between the evaluation system...
of the VPP and PEVs, PV systems, gas turbines, and flexible loads.

For a VPP, PEVs can be utilised as a distributed energy storage system. Through the charging and discharging of energy storage, the bidirectional transmission of electrical energy between the electric vehicles and the power grid can be realised, that is, charging and storing energy for the PEV battery during off-peak hours, and feeding electrical energy back to the power grid during peak hours. V2G enables the PEV fleet to be aggregated into an energy storage system, wherein each PEV is equivalent to a controllable energy storage device with a flexible charging/discharging rate. Through the reasonable scheduling of PEVs, the VPP can accommodate the surplus energy from renewable resources, achieve peak shaving, and reduce the reserve demand, thus producing economic and environmental benefits.

In order to fully exploit the flexible adjustment ability of PEVs, the evaluation system considers the operation of the VPP participating in the two-stage market, when making an economic evaluation. Owing to the relatively small capacity of VPPs, they are regarded as price receivers. In the day-ahead market, the evaluation system of the VPP should submit energy bids (only quantity) per hour [4] according to the predicted day-ahead and real-time market prices provided by the information system. The evaluation system sends the dispatch instructions of relevant components of the VPP through the information system. Taking into consideration the random fluctuations of PEVs, PV output, and load demand, and any sudden reduction in generation caused by a fault [22], the VPP needs to participate in the real-time market to maintain a balance. In the real-time market, the information system collects the energy deviations from the energy bids in the day-ahead market and submits them to the evaluation system. Through the evaluation system, the VPP operator purchases the difference between the actual real-time energy delivery and the predicted demand to make up for the deviations in the day-ahead bidding.

The two-stage market of the VPP adopts the two-settlement mechanism for the financial settlement of energy deliveries:

\[
R_{s,t}^{\text{VPP}} = \lambda_s^{\text{DA}} P_s^{\text{DA}} + \lambda_s^{\text{RT}} (P_s^{\text{RT}} - P_s^{\text{DA}}) \quad \forall s, t \tag{1}
\]

where \(R_{s,t}^{\text{VPP}}\) represents the revenue of the VPP from electricity markets; \(\lambda_s^{\text{DA}}\) and \(\lambda_s^{\text{RT}}\) are the day-ahead and real-time market prices, respectively; \(P_s^{\text{DA}}\) indicates the energy bid of the VPP in time slot \(t\) in the day-ahead market; \(P_s^{\text{RT}}\) is a scenario-related variable and represents the real-time delivery of the VPP in scenario \(s\) and time slot \(t\).

Compared to the financial settlement of the individual day-ahead and real-time markets, the evaluation system of the VPP considers both the revenue of the day-ahead market and the cost caused by real-time energy deviations, which can provide a superior bidding strategy.

3 | MODEL OF PLUG-IN ELECTRIC VEHICLES IN VPP

In this section, the charging and discharging model of PEVs in the VPP is established, and based on the uncertainty of the PEV charging/discharging behaviour, the charging station model is formulated in detail. For simplification, the decision variables and parameters related to PEVs are presented without the subscript for scenarios in this section. Note that we have considered the uncertainties in the charging load requirement, arrival time and departure time in the optimal bidding model in Section 4.

3.1 | Charging/discharging model of PEVs

The connection states of PEVs and the VPP are classified as charging and discharging. The lithium-ion battery is a typical power battery for electric vehicles, whose physical mechanism of discharging is symmetrical with the charging process. Therefore, the charging process of PEVs is selected for analysis.

To prolong the battery lifespan, the charging process of PEVs consists of a constant current (CC) stage and a constant voltage (CV) stage [23]. When the state of charge (SOC) of the battery is relatively low, that is, it is less than a specific state of charge \(\text{SOC}_{\text{CC}}\), the battery current remains constant. In the CC stage, the voltage increases continuously, and the maximum charging power, denoted by \(P_{\text{PEVmax}}\), is constant. When the SOC of the battery reaches \(\text{SOC}_{\text{CV}}\), the voltage increases to its maximum value \(V_{\text{PEVmax}}\). Then, in order to prevent battery damage, the charging process is converted to the CV stage, which lasts until the battery is fully charged.

In the CV stage of PEV battery charging, the voltage remains at the maximum value, and the current decreases exponentially, following the ampere-hour law:

\[
P_{\text{PEV}}^{\text{CV}} = P_{\text{PEVmax}} e^{-\epsilon / \tau}, \quad \tau > 0 \tag{2}
\]
where $P^i_{\text{PEV}}$ is the current of the $i$th PEV battery; $I^i_{\text{PEV},\text{max}}$ is the maximum current; and $\varepsilon_i$ represents a parameter of the PEV battery cell. Assuming that the charging and discharging efficiency of the PEV battery are the same, both denoted by $\eta^i_{\text{PEV}}$, the battery cell parameter $\varepsilon_i$ can be expressed as follows:

$$\varepsilon_i = \frac{\eta^i_{\text{PEV}} P^i_{\text{PEV},\text{max}}}{E^i_{\text{PEV},\text{max}} (1 - \text{SOC}_i^C)}$$

where $E^i_{\text{PEV},\text{max}}$ indicates the capacity of the PEV battery pack, and $\text{SOC}_i^C$ represents the SOC for CC to CV mode switching in the charging process, in pu.

The maximum charging power $P^i_{\text{PEV},\text{max}}$ of the $i$th PEV in time slot $t$ can be expressed as the product of $V^i_{\text{PEV},\text{max}}$ and $I^i_{\text{PEV},t}$.

$$P^i_{\text{PEV},\text{max}} = V^i_{\text{PEV},\text{max}} I^i_{\text{PEV},t} = V^i_{\text{PEV},\text{max}} P^i_{\text{PEV},\text{max}} \varepsilon_i - \varepsilon_i = P^i_{\text{PEV},\text{max}} \varepsilon_i - \varepsilon_i$$

According to the above equation, the maximum charging power decreases exponentially in the CV stage.

During the CV stage, the state of charge $\text{SOC}^i_{\text{PEV}}$ in time slot $t$ can be expressed as the integral of the charging power:

$$\text{SOC}^i_{\text{PEV}} = \text{SOC}_i^C + \frac{\eta^i_{\text{PEV}}}{E^i_{\text{PEV},\text{max}}} \int_0^t P^i_{\text{PEV},\text{max}} d\tau$$

Based on Equations (4) and (5), $\text{SOC}^i_{\text{PEV}}$ can be calculated as:

$$\text{SOC}^i_{\text{PEV}} = \text{SOC}_i^C + \frac{\eta^i_{\text{PEV}}}{E^i_{\text{PEV},\text{max}}} \left( P^i_{\text{PEV},\text{max}} - P^i_{\text{PEV},\text{max}} \right)$$

By substituting Equation (3) into Equation (6), it can be deduced that:

$$p^i_{\text{PEV},\text{max}} = P^i_{\text{PEV},\text{max}} \frac{1 - \text{SOC}^i_{\text{PEV}}}{1 - \text{SOC}_i^C}$$

Furthermore, in the form of piecewise linearisation, the maximum charging power of the entire charging process can be expressed as:

$$p^i_{\text{PEV},\text{max}} = \begin{cases} 
P^i_{\text{PEV},\text{max}}, & 0 \leq \text{SOC}^i_{\text{PEV}} \leq \text{SOC}_i^C, \\
\frac{P^i_{\text{PEV},\text{max}} - \text{SOC}^i_{\text{PEV}}}{1 - \text{SOC}_i^C}, & \text{SOC}_i^C < \text{SOC}^i_{\text{PEV}} \leq 1.
\end{cases}$$

Similarly, the maximum discharging power of the entire discharging process can be expressed as:

$$p^i_{\text{PEV},\text{max}} = \begin{cases} 
P^i_{\text{PEV},\text{max}}, & 0 \leq \text{SOC}^i_{\text{PEV}} \leq \text{SOC}_i^D, \\
\frac{P^i_{\text{PEV},\text{max}}}{\text{SOC}^i_{\text{PEV}}} \frac{\text{SOC}^i_{\text{PEV}} - \text{SOC}^i_{\text{PEV}}}{\text{SOC}_i^D}, & \text{SOC}_i^D < \text{SOC}^i_{\text{PEV}} \leq 1.
\end{cases}$$

where $\text{SOC}_i^D$ is the SOC for the CC to CV mode switching in the discharging process, in pu.

The charging and discharging power boundaries limit the instantaneous charging/discharging power of PEVs. Based on the above analysis, the dispatching feasible region of V2G is depicted in Figure 2, reflecting the controllable charging and discharging power boundaries of PEVs.

### 3.2 Model of a charging station

Modelling each PEV in the VPP as a virtual battery, the charging station can be formulated as an aggregator of batteries in the PEV fleet. The operation of the charging station depends on the SOC and the charging/discharging efficiency of each PEV. The behaviour of each PEV in the VPP is characterised by the arrival time ($T^i_a$), departure time ($T^i_d$), initial SOC ($\text{SOC}^i_a$), and target SOC ($\text{SOC}^i_d$).

The VPP should consider the uncertainty caused by the random behaviour of a single PEV owner when dispatching
electric vehicles. According to [24], it is assumed that the initial SOC $SO_{C_{i}}$, arrival time $T_{a_{i}}$, and departure time $T_{d_{i}}$ of PEVs conform to a Gaussian distribution, where $N(\mu, \sigma^{2})$ denotes a Gaussian distribution with mean $\mu$ and standard deviation $\sigma$. The corresponding probability density functions and relevant parameter settings are shown in Figures 3 and 4.

A stochastic programming model based on multiple scenarios [25] is adopted to describe the characteristics representing the behaviour of PEVs. The PEV scenarios are generated by combining the corresponding probability density functions. Consider $\Phi = \{1, 2, ..., N^{\Phi}\}$ representing the set of scenarios, where $N^{\Phi}$ denotes the number of scenarios and $\gamma_{i}$ denotes the probability of scenario $i$.

The power of a charging station in the VPP is related to the number of PEVs arriving at the station and is time-varying. The PEVs are aggregated as a set of PEV batteries and denoted by $\Phi_{PEV} = \{1, 2, ..., N^{PEV}\}$, where $N^{PEV}$ is the number of PEVs.

The model of a charging station can be described as follows:

$$P_{C_{SC}} = \sum_{i \in \Phi_{PEV}} P_{P_{i}^{PEV}, C_{SD}} = \sum_{i \in \Phi_{PEV}} P_{P_{i}^{PEV}, D_{i}}^{PEV}, \forall t \quad (10)$$

$$p_{C_{SC}}^{PEV}, p_{C_{SD}}^{PEV} \in [0, 1], \forall i, t \quad (11)$$

$$0 \leq P_{i}^{PEV} \leq C_{SD_{i}}^{PEV}, \forall i, t \quad (12)$$

$$0 \leq P_{i}^{PEV} \leq \frac{1 - \phi_{i}^{PEV} P_{i}^{PEV} SOC_{i}^{PEV}}{1 - SOC_{i}^{PEV}}, \forall i, t \quad (13)$$

$$0 \leq P_{i}^{PEV} \leq \phi_{i}^{PEV} P_{i}^{PEV}, \forall i, t \quad (14)$$

$$0 \leq P_{i}^{PEV} \leq \phi_{i}^{PEV} P_{i}^{PEV}, \forall i, t \quad (15)$$

$$\phi_{i}^{PEV} = \begin{cases} 0, & t < T_{a_{i}} \text{ or } t > T_{d_{i}} \\ 1, & T_{a_{i}} \leq t \leq T_{d_{i}} \end{cases} \quad (16)$$

$$SOC_{i,t}^{PEV} = SOC_{i,t-1}^{PEV} + \frac{1}{E_{i}^{PEV}} \left( \eta_{i}^{PEV} P_{i}^{PEV} - \frac{P_{i}^{PEV-1}}{\eta_{i}^{PEV}} \right) \quad (17)$$

$$SOC_{i,t}^{PEV} = SOC_{i,T_{d_{i}}}^{PEV} \geq SOC_{i,t}^{PEV}, \forall i \quad (18)$$

$$SOC_{i,t}^{PEV} \in [0, 1], \forall i, t \quad (19)$$

where $p_{C_{SC}}^{PEV}$ and $p_{C_{SD}}^{PEV}$ are the total charging power and discharging power, respectively; $P_{i}^{PEV}$ and $P_{i}^{PEV}$ are the charging power and discharging power of the $i$th PEV, respectively; $C_{SD_{i}}^{PEV}$ is the capacity of the charging station; and $\phi_{i}^{PEV}$ is a parameter indicating the plug-in status of the $i$th PEV.

Constraint (10) indicates the aggregated relationship between the charging station and PEVs in the VPP, and the capacity of the charging station is given in (11). Note that the limits of charging and discharging power of PEVs can be formulated as constraints (12) to (15). Constraint (16) determines the plug-in status of an individual PEV. The law of energy conservation of the PEV battery is described in (17). According to constraint (18), the initial SOC is set as the SOC of the PEV at arrival time, and the SOC at departure time should be greater than the target SOC.

Considering the charging and discharging power of different PEVs, the power limits and cumulative energy limits of PEVs in the VPP are proposed in an aggregation model of PEVs. In the VPP, the charging station collects a set of information for each PEV, including the arrival time, departure time, initial SOC and target SOC, and submits these parameters as well as the
aggregated information of power limits and accumulated energy limits to the VPP operator.

4 | OPTIMAL BIDDING MODEL OF THE VPP

The VPP is composed of distributed generators, conventional thermal power plants, flexible loads, and energy storage systems. Based on the physical relationship and information exchange among the components of the VPP, an optimal bidding model of the VPP considering the V2G mode is proposed herein. In this model, a two-stage stochastic programming method based on multiple scenarios is used to describe the uncertain characteristics of PEVs, PV output, load demand, and market prices.

The aim of the objective function is to achieve the maximum total revenue of the VPP. The mathematical model of the relevant components in the VPP is reasonably linearised, and the commercial solver CPLEX is used for determining the optimal bidding of the VPP.

4.1 | Objective function

In this section, the economic benefits of the VPP are presented, considering its participation in the two-stage market trading. According to the forecast day-ahead and real-time market prices, the evaluation system of the VPP can submit hourly energy bidding in the day-ahead market while anticipating real-time market purchases. The evaluation system of the VPP settles the deviation cost between the real-time delivery and the day-ahead bidding according to the real-time price, so as to take into account both the revenue in the day-ahead market and the cost caused by the deviation in the real-time market.

The bidding strategy of the VPP consists of three terms: the expected revenues of the day-ahead market, the settlement revenues of the real-time market, and the real-time generation operational costs, as expressed below:

$$\max_{\mathbf{x}^{DA}, \mathbf{x}^{RT}} R^{DA} + R^{RT} - C^{RT}$$ (20)

where the decision variables $\mathbf{x}^{DA}$ and $\mathbf{x}^{RT}$ represent the day-ahead- and real-time-related variables, respectively. The three terms of the bidding strategy can be calculated as:

$$R^{DA} = \sum_{i \in \Phi^P} a^{DA}_i p^{DA}_i$$ (21)

$$R^{RT} = \sum_{i \in \Phi^P} \sum_{i \in \Phi^F} A^{RT}_{i,t} (p^{RT}_{i,t} - p^{DA}_{i,t})$$ (22)

$$C^{RT} = \sum_{i \in \Phi^P} \sum_{i \in \Phi^P} \sum_{i \in \Phi^T} \sum_{i \in \Phi^{MT}} \gamma_{i,s,t} p^{MT,RT}_{i,s,t}$$ (23)

where $p^{MT,RT}_{i,s,t}$ represents the real-time power of the $i$th gas-fired micro-turbine (MT) in scenario $s$ and slot $t$.

4.2 | Constraints

The constraints of the VPP bidding strategy include the power constraints and energy constraints of the PEV fleet, PV systems, gas-fired MTs, and power load. The constraints are expressed in the day-ahead and real-time stages as follows:

(i) Power balance:

$$p^{DA}_{i,s,t} = \sum_{i \in \Phi^P} p^{PV,DA}_{i,s,t} + \sum_{i \in \Phi^F} p^{MT,DA}_{i,s,t} + p^{CSD,DA}_{i,s,t} - p^{CSC,DA}_{i,s,t} - p^{ADJ}_{i,s,t}, \forall i, t$$ (24)

$$p^{RT}_{i,s,t} = \sum_{i \in \Phi^P} p^{PV,RT}_{i,s,t} + \sum_{i \in \Phi^F} p^{MT,RT}_{i,s,t} + p^{CSD,RT}_{i,s,t} - p^{CSC,RT}_{i,s,t} - p^{ADJ}_{i,s,t}, \forall i, s, t$$ (25)

$$p^{DA}_{i,s,t}, p^{RT}_{i,s,t} \in [-p^{PV,DA}_{i,s,t}, p^{PV,DA}_{i,s,t}], \forall i, t$$ (26)

where $p^{PV,DA}_{i,s,t}$ and $p^{MT,DA}_{i,s,t}$ are the power of the $i$th PV or MT in time slot $t$, respectively; $p^{CSC,DA}_{i,s,t}$ and $p^{CSD,DA}_{i,s,t}$ are the charging and discharging power of the station in time slot $t$, respectively; and $p^{ADJ}_{i,s,t}$ is the load demand of the VPP in time slot $t$. The associated variables with the superscript "RT" are similar in scenario $s$ and slot $t$.

(ii) PEV fleet limit:

The constraints of the PEV fleet are divided into charging and discharging power constraints and energy accumulation constraints, as detailed from (10) to (19) in Section 2.

(iii) PV power limit:

$$p^{PV,DA}_{i,s,t} \in [0, p^{PVF,DA}_{i,s,t}], \forall i, t$$ (27)

$$p^{PV,RT}_{i,s,t} \in [0, p^{PVF,RT}_{i,s,t}], \forall i, s, t$$ (28)

where $p^{PVF,DA}_{i,s,t}$ and $p^{PVF,RT}_{i,s,t}$ are the day-ahead forecasted power and real-time scenario-related forecast, respectively; and $\Phi^{PV}$ is the set of PV systems.

(iv) MT power limit:

$$-\delta^{ADJ}_{i,t} p^{MT,ADJ}_{i,s,t} \leq p^{MT,DA}_{i,s,t} - p^{MT,RT}_{i,s,t} \leq \delta^{ADJ}_{i,t} p^{MT,ADJ}_{i,s,t}\max$$ (29)

$$p^{MT,DA}_{i,s,t}, p^{MT,RT}_{i,s,t} \in [0, p^{MT,\max}_{i,\max}], \forall i, s, t$$ (30)

where $p^{MT,\max}_{i,\max}$ is the capacity of the $i$th MT, $\delta^{ADJ}_{i,t}$ is the limit of real-time power adjustment of the $i$th MT, and $\Phi^{MT}$ is the set of MTs.
(v) Load demand limit:

\[
\sum_{t \in \Phi^D} p^D_{t} \geq E^D_{\min} \quad (31)
\]

\[
\sum_{t \in \Phi^D} p^D_{t} \leq E^D_{\max} \forall t \quad (32)
\]

\[
p^D_{t} \in [p^D_{\min}, p^D_{\max}], \forall t \quad (33)
\]

\[
p^{RT}_{t} \in [p^{RT}_{\min}, p^{RT}_{\max}], \forall s, t \quad (34)
\]

where \(E^D_{\min}\) and \(E^D_{\max}\) are the day-ahead and real-time daily load demand, respectively; \(p^D_{\min}\), \(p^D_{\max}\), \(p^{RT}_{\min}\), and \(p^{RT}_{\max}\) are the day-ahead and real-time minimum and maximum load, respectively, and \(\Phi^D\) is the set of time slots.

(vi) Distribution network limit:

In the design of a VPP, the importance of a secure distribution network operation should be fully acknowledged. In order to facilitate the solution of the mixed integer programming model, a linearised power flow method of the distribution network [26] is adopted. Without considering the network loss, the power flow equation is approximated to the following form:

\[
p^D_{bq, t} = \frac{V_{bq}^{DA} - V_{gq}^{DA}}{2} - b_{bq}(\theta_{bq}^{DA} - \theta_{gq}^{DA}), \forall t \quad (35)
\]

\[
Q^D_{bq, t} = -b_{bq} - \frac{V_{bq}^{DA} - V_{gq}^{DA}}{2} - \theta_{bq}^{DA} - \theta_{gq}^{DA}), \forall t \quad (36)
\]

\[
p^{RT}_{bq, s, t} = \frac{V^{RT}_{bq} - V^{RT}_{gq}}{2} - b_{bq}(\theta^{RT}_{bq} - \theta^{RT}_{gq}), \forall s, t \quad (37)
\]

\[
Q^{RT}_{bq, s, t} = -b_{bq} - \frac{V^{RT}_{bq} - V^{RT}_{gq}}{2} - \theta^{RT}_{bq} - \theta^{RT}_{gq}), \forall s, t \quad (38)
\]

where \(p^D_{bq, t}\) and \(Q^D_{bq, t}\) represent the day-ahead active and reactive power of the line between nodes \(b\) and \(g\), respectively; \(b_{bq}\) and \(g_{bq}\) are the susceptance and conductance values of the line between nodes \(b\) and \(g\), respectively; and \(V^{DA}\) and \(\theta^{DA}\) are the day-ahead amplitude and phase angle of the node voltage. The associated variables with the superscript ‘RT’ are similar in scenario \(s\) and slot \(t\).

Line power constraints can be approximated in the following piecewise linear form:

\[
p^D_{bq, t} \cos \frac{2\pi k}{N} + Q^D_{bq, t} \sin \frac{2\pi k}{N} \leq S^D_{bq, t} \cos \frac{\pi}{N}, \quad k \in 1, 2 \ldots N, \forall t \quad (39)
\]

\[
p^{RT}_{bq, s, t} \cos \frac{2\pi k}{N} + Q^{RT}_{bq, s, t} \sin \frac{2\pi k}{N} \leq S^{RT}_{bq, s, t} \cos \frac{\pi}{N}, \quad k \in 1, 2 \ldots N, \forall s, t \quad (40)
\]

FIGURE 5  Flow chart of the annual simulation of the VPP operation

where \(S^D_{bq, t}\) is the apparent power limit of the line between nodes \(b\) and \(g\), and \(N\) is the number of segments.

4.3  Annual simulation of the VPP operation

The optimal bidding model of the VPP is proposed based on the day-ahead and real-time two-stage market trading. Assuming that the load demand and external natural environment exhibit no violent fluctuations, and the influence of the medium and long-term contract market is not considered, the specific process of simulating the annual operation of the VPP is demonstrated in Figure 5 as follows.

(i) Initialize the data of the VPP on day \(t\). The market prices, PV output, and load data are generated using the stochastic programming method based on multiple scenarios.

(ii) Determine the evaluation parameters of PEV behaviour as \(T_{i}^{d}, T_{i}^{a}, S O C_{i}^{d},\) and \(S O C_{i}^{a}\) of each PEV and generate the behaviour information of the PEV fleet using Monte Carlo simulation. According to the historical data of evaluation parameters, the probability distribution models...
of parameters can be constructed to conduct a random simulation.

(iii) According to the charging and discharging model of PEVs, the dispatching feasible region of each PEV can be calculated under constraints (12) to (19).

(iv) According to the overall constraints of the VPP, the hourly energy bids in the day-ahead market and energy procurements in the real-time market are calculated.

(v) The objective function, that is, the total revenue of the VPP, is evaluated. Using Equations (21) to (23), the optimal bidding strategy considering the day-ahead revenues and real-time energy deviations is obtained.

(vi) The operational data of the VPP on day \( t \) are computed. The data include day-ahead revenues, real-time settlement revenues, real-time generation operational costs, and total solar energy consumption per day. The program runs simulations and formulates statistics till the end of \( T \) days.

5 | CASE STUDIES

5.1 | Data description

The test environment of the case studies was a computer with a 2.40 GHz CPU and 16 GB RAM, and MATLAB R2016a. We set up a VPP that aggregates 60 PEVs, 5 PV systems, and 5 MTs.

As shown in Figure 6, the improved IEEE-33 distribution network with 24-h time slots was studied. The electricity market prices and power load data were obtained from the PJM market [27]. Given the uncertainty of the electricity market prices, PV, loads, and other factors, 10 scenarios were generated by k-means clustering from the annual data and probability distributions. Solar energy data were collected from the National Renewable Energy Laboratory [28]. The data as of 21 March 2019 (shown in Figure 7) were considered as data of a typical day. The charging and discharging efficiency of the electric vehicle was 95%, and the maximum power was 5 kW. \( \text{SOC}_C^i \) and \( \text{SOC}_D^i \) were set to 0.8 and 0.2, respectively [29]. The installed capacity of each MT was 50 kW, and the operating cost was 0.055, 0.065, 0.075, 0.085, and 0.095 $/kWh, respectively. The real-time adjustment limit of each MT was 10%. The hourly adjustment range of power load was set to 0.9 times and 1.1 times of the original data. The maximum bidding capacity of the VPP was 250 kW.

In order to demonstrate the effectiveness and market benefits of the VPP framework proposed, the following three strategies were compared in the case study.

S1: In this strategy, the PEVs in the VPP support the V2G mode to feed electrical energy back to the grid, and the charging/discharging rates can be flexibly regulated in response to the dispatch instructions from the information system;

S2: This strategy does not support the V2G mode, but can alter the charging rates of the PEVs;

S3: This strategy does not consider the information interaction of the VPP, which is the traditional energy aggregation mode. In this strategy, the PEVs will be charged according to the highest charging rate immediately after arriving at the station.
5.2 | Optimal bidding strategy

The day-ahead optimal bidding strategies of the VPP are shown in Figure 8.

S1 has more surplus power available for bidding than S2 and S3, especially during peak hours from 7:00 a.m. to 10:00 a.m.

The hourly solar energy accommodation and the day-ahead bidding strategies of PEVs are shown in Figure 9. In the bidding strategies of PEVs, the y-axis represents the difference between the discharge and charge energy. When PEVs discharge to the grid, the energy is positive; otherwise, it is negative.

The results indicate that S1 can accommodate more solar energy than S2 and S3. S1 realised variable-rate and flexible charging/discharging of PEVs through V2G technology in response to the VPP dispatching instructions. In S1, the PEVs charged from 0:00 to 5:00, when the market price was low; then, the PEVs charged from 11:00 to 17:00 when solar energy was abundant. From 6:00 to 10:00 and from 18:00 to 24:00 are the two peak periods of load demand in the VPP, and also the two peaks in the electricity price. During these periods, in order to satisfy the load demand of the VPP and to reduce the power consumption cost, PEVs discharge to the grid and coordinate the operation of the MTs, so as to achieve a balance between supply and demand. In S2, the PEV can only adjust the charging rate, and hence PEVs should avoid charging during the peak hours of load demand and electricity price as much as possible, and charge at noon to accommodate more solar energy. In S3, without the control of an information system, PEVs charge at the highest charging rate immediately after arriving at the station, which causes problems—a large number of PEVs charge during peak hours, increasing the cost of the VPP operation.

Taking into account the day-ahead and real-time markets, Table 1 compares the economic benefits of the three strategies. The results show that, in S1, because the VPP can adjust the charging/discharging rates of PEVs and support PEVs to feed electric energy back to the grid, PEVs can accommodate more solar energy at noon and enhance the resource utilisation ratio of the VPP. Furthermore, PEVs can replace MTs in the power supply during peak hours, which can significantly reduce operating costs, reduce greenhouse gas emissions, and generate economic and environmental benefits.

5.3 | Annual analysis of bidding strategies

The actual operation of a VPP is affected by the weather, market price, production, life, and other factors. Among these factors, the weather directly affects the output of PV systems [30], further influencing the bidding strategy of the VPP in electricity markets. In order to observe the bidding changes in different scenarios with various market prices, and to gain a more comprehensive understanding of the operation revenues of VPPs participating in the spot market under various environmental conditions, an annual simulation was conducted. Assuming that medium- and long-term market effects were not considered, the annual data of 2019 were analysed. The annual solar energy accommodation curves and annual VPP revenue curves are presented in Figures 10 and 11, respectively.

To facilitate the analysis of the annual changes in the VPP, four typical days of spring equinox (SE), summer solstice (SS), autumn equinox (AE), and winter solstice (WS) were selected for comparison. The accommodation of solar energy and the VPP revenues under the three different strategies are listed in Table 2.

As indicated by the table, S1 is the optimal strategy for the operation of VPPs on the days of SE, SS, AE, and WS. When the VPPs operate according to this strategy, the solar radiation on the SS is the largest, thus the solar energy output is the largest. At the same time, the accommodation of solar energy in the VPP reaches its maximum. On the SS, owing to the larger daily load demand, the output of the MTs is increased and the operational cost of the VPP is increased. On the WS, the solar radiation of the VPP is the smallest and the energy accommodation is the least. On the SE and AE, the storage capacity of the PEVs and load requirements of the VPP were adequate to accommodate solar energy, and the load demand was not too large. Therefore, the revenues on the SE and AE were higher than those on the other days. According to the historical electricity price data of 2019, the marginal price of each hour on the AE was generally lower than that of the SE. Consequently, the electricity price was beneficial to the revenue of the day-ahead and real-time markets, thus the revenue of the VPP on the AE was the highest.

| TABLE 1 | Typical daily market revenues of the three strategies |
|---------|-----------------------------------------------|
| Revenue-strategy | S1  | S2  | S3  |
| Day-ahead  | $6.63 | $−28.39 | $−32.80 |
| Real time   | $20.68 | $3.42  | $−0.71  |
| Total       | $27.31 | $−24.97 | $−33.51 |
5.4 Impacts of the feasible region of V2G

In the process of constructing the optimal bidding strategy framework of the VPP, the V2G dispatching feasible region of a PEV is detailed along with the charging and discharging characteristics of the PEV battery. However, the conventional model of the V2G mode of PEVs typically lacks constraints (13) and (15), as illustrated in Figure 12, and the CC and CV stages in the charging and discharging process of the PEV battery are ignored. There is a problem in that PEVs may fail to be dispatched in the actual operational stage, and a battery failure may be caused by internal polarisation of the battery.

**TABLE 2** Solar energy accommodation and VPP revenues on four typical days

|      | S1          |               | S2           |               | S3           |               |
|------|-------------|---------------|-------------|---------------|-------------|---------------|
|      | Day         | PV (kWh)      | Revenue ($) | PV (kWh)      | Revenues ($) | PV (kWh)      | Revenue ($)   |
| SE   | 6617.1      | 27.31         |             | 5860.4        | −24.97       | 5299.6        | −33.51        |
| SS   | 6627.3      | 20.88         |             | 5973.3        | −12.93       | 5299.6        | −16.47        |
| AE   | 6614.7      | 35.89         |             | 5869.0        | 4.26         | 5290.7        | 0.88          |
| WS   | 4133.3      | 22.88         |             | 3934.6        | −33.09       | 2901.3        | −37.28        |
In Figure 13, the day-ahead bidding strategies of the PEV fleet in the VPP are compared under two bidding strategies, with the limits of the CC and CV stages (CC-CV limits) and without CC-CV limits in the charging/discharging process. Considering CC-CV limits, the charging/discharging power of the PEV fleet is limited by the maximum power $P_{\text{PEV}}^{i,t,\text{max}}$ and is also linearly constrained with the SOC in the same time slot $t$. Therefore, the fluctuation amplitude of the day-ahead bidding energy of the PEV fleet with CC-CV limits is smaller than that of the day-ahead bidding energy without CC-CV limits.

From the results, the total daily revenue of the bidding strategy with CC-CV limits was $27.31$, and the solar energy accommodation was $6917.1 \text{ kWh};$ the total daily revenue of the bidding strategy without CC-CV limits was $32.24$, and the solar energy accommodation was $6910.5 \text{ kWh}$. In the actual operation of the VPP, in order to prevent any damage to the battery structure caused by overcharging, the bidding strategy of the VPP without considering CC-CV limits has to reduce the solar energy accommodation by $5.69\%$. The extra revenue of $4.93$ will not be obtained from the electricity market, which would lead to large deviations of the bidding strategy.

Therefore, it is necessary to determine the relationship between the battery charging/discharging power and the SOC, combined with the charging/discharging characteristics of the PEV battery and the CC-CV limits. The detailed dispatching feasible region of V2G proposed can ensure the accuracy of the optimal bidding strategy of the VPP and avoid deviations of the day-ahead bidding for the PEV fleet.
5.5 Impacts of the PEV penetration

Different levels of PEV penetration have a significant impact on the available storage capacity of the VPP. In this section, the accommodation of solar energy and the annual revenues of the VPP in S1 are presented according to different numbers of PEVs.

Figure 14 shows that for VPPs, V2G technology is an effective means to accommodate renewable energy and improve economic benefits. When the number of PEVs in the VPP is relatively small, the total storage capacity of the PEVs is small, thus less solar energy can be transferred at peak hours or night-time. When the operation and maintenance costs of PEVs are not taken into account, with the increase in the number of PEVs, the solar energy daily regulation capacity is enhanced, and more PEVs can discharge for power supply during the peak hours of the VPP, so that the VPP can obtain higher annual revenues.

Compared to the situation with no PEVs, the annual solar energy accommodation of the VPP with 120 PEVs increased by 30.12%, and the annual revenue improved significantly. However, when the number of PEVs was above 90, the consumption demand of solar energy was diluted, and the storage capacity of PEVs was sufficient to satisfy the accommodation of solar energy in the VPP. As a result, the revenue did not increase much with the increase in the number of PEVs from 90 to 120.

Therefore, access to more PEVs does not always imply higher market revenues for the VPP. Within a certain penetration range of PEVs, the increase in the number of PEVs can accommodate more solar energy and bring more economic benefits to the VPP.

6 CONCLUSION

A detailed model based on the V2G mode was established to describe the charging/discharging behaviour of PEVs, and an optimal bidding framework was proposed for the VPP that aggregates power generation systems, flexible loads, and energy storage systems. We analysed the operational mechanism of the VPP, and realised the optimal bidding for it. By comparing the three strategies, the case studies demonstrate that:

(i) The optimal bidding strategy for the VPP proposed significantly reduced the market operational cost and the power purchase cost by more than 10% based on the analysis of the annual data. Moreover, V2G technology can feed electrical energy back to the power grid to obtain additional economic benefits.

(ii) The V2G technology and the VPP information system can realize flexible charging and discharging between PEVs and the power grid, so as to effectively accommodate the renewable energy in the VPP. The relationship between the charging/discharging power and the SOC under the CC and CV charging/discharging modes was clarified, and the accurate dispatching feasible region of V2G was constructed, which ensured the accuracy of the optimal bidding strategy of the VPP.

(iii) In the VPP, within a certain penetration range of PEVs, the increase in the number of PEVs can enhance the accommodation of solar energy. Every percentage point increase in the penetration rate of PEVs increased the annual solar energy accommodation of the VPP by nearly 0.6%. A VPP that supports the V2G mode can coordinate the contradiction between massive DERs supply and the secure and economic operation of the power grid, so as to obtain added market benefits.

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REFERENCES

1. Wang, J. et al.: Incentive mechanism for sharing distributed energy resources. J. Mod. Power Syst. Clean Energy 7(4), 837–850 (2019)
2. Awerbuch, S., Carayannis, E.G., Preston, A.: In: The Virtual Utility: Some Introductory thoughts on Accounting, Learning and the Valuation of Radical Innovation, pp. 71–76. Springer, Germany (1997)
3. Mashhour, E., Moghaddas-Tafreshi, S.M.: Bidding strategy of virtual power plant for participating in energy and spinning reserve markets—Part I: Problem formulation. IEEE Trans. Power Syst. 26(2), 949–956 (2011)
4. Wang, J. et al.: Incentivizing distributed energy resource aggregation in energy and capacity markets: An energy sharing scheme and mechanism design. Appl. Energy 252, 113471 (2019)
5. Xu, Z. et al.: Virtual power plant-based pricing control for wind/thermal cooperated generation in China. IEEE Trans. Syst. Man Cybern. Syst. 46(5), 706–712 (2016)
6. Koraki, D. and Strunz, K.: Wind and solar power integration in electricity markets and distribution networks through service-centric virtual power plants. IEEE Trans. Power Syst. 33(1), 473–485 (2018)
7. Wang, J. et al.: Reliability value of distributed solar+storage systems amidst rare weather events. IEEE Trans. Smart Grid 10(4), 4476–4486 (2019)
8. Fleten, S.E., Maribu, K.M., Wangensteen, I.: Optimal investment strategies in decentralized renewable power generation under uncertainty. Energy 32(5), 803–815 (2007)
9. Wang, J. et al.: Reliability value of distributed solar+storage systems amidst rare weather events. IEEE Trans. Smart Grid 10(4), 4476–4486 (2019)
10. Zhang, H. et al.: Evaluation of achievable vehicle-to-grid capacity using aggregate PEV model. IEEE Trans. Power Syst. 33(2), 1628–1636 (2012)
11. Aluisio, B. et al.: Optimal operation planning of V2G-equipped Microgrid in the presence of EV aggregator. Electr. Power Syst. Res. 152, 295–305 (2017)
12. Zhang, M. et al.: Research on regional vehicle-to-grid operation mode and optimal share planning model integrating it into electric power system. Power Syst. Technol. (06), 181–187 (2012)
13. Egbeie, O., Uko, C.: Multi-agent approach to modeling and simulation of microgrid operation with vehicle-to-grid system. Electr. J. 33(3), 106714 (2020)
14. Guo, H. et al.: Optimal scheduling model of virtual power plant in a unified electricity trading market. Trans. China Electrotechnical Soc. 30(23), 136–145 (2015)
15. Zhang, H. et al.: Evaluation of achievable vehicle-to-grid capacity using aggregate PEV Model. IEEE Trans. Power Syst. 32(1), 784–794 (2017)
16. Guo, H. et al.: Optimal scheduling model of virtual power plant in a unified electricity trading market. Trans. China Electrotechnical Soc. 30(23), 136–145 (2015)
17. Xu, Z. et al.: A hierarchical framework for coordinated charging of plug-in electric vehicles in China. IEEE Trans. Smart Grid 7(1), 428–438 (2017)
18. Zhang, H. et al.: Evaluation of achievable vehicle-to-grid capacity using aggregate PEV Model. IEEE Trans. Power Syst. 32(1), 784–794 (2017)
19. Wang, X. et al.: Operation mechanism and key technologies of virtual power plant under ubiquitous internet of things. Power Syst. Technol. 43(09), 3175–3183 (2019)
20. Bessa, R.J. et al.: Optimized bidding of a EV aggregation agent in the electricity market. IEEE Trans. Smart Grid 3(1), 443–452 (2012)
21. Wu, Z. et al.: Profit-sharing mechanism for aggregation of wind farms and concentrating solar power. IEEE Trans. Sustain. Energy 11, 2606–2616 (2020)
22. Yang, Z. et al.: A linearized opf model with reactive power and voltage magnitude: A pathway to improve the mw-only dc opf. IEEE Trans. Power Syst. 33(2), 1734–1745 (2018)
23. PJM Day-Ahead Hourly LMPs website. https://dataminer2.pjm.com/feed/da_hrl_lmps, Accessed December 2019
24. NREL PVWatts Calculator website. https://pvwatts.nrel.gov/, Accessed December 2019
25. Zhang, P. et al.: A methodology for optimization of power systems demand due to electric vehicle charging load. IEEE Trans. Power Syst. 27(3), 1628–1636 (2012)
26. Wang, J. et al.: Exploring key weather factors from analytical modeling toward improved solar power forecasting. IEEE Trans. Smart Grid 1–1 (2017)

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