A Novel Model for VPP to Participate in Capacity Market Auction

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Abstract. With the development of intermittent renewable energy, power system needs more capacity resources to ensure the generation adequacy during peak load periods. Flexible resources such as electric vehicles (EVs) and demand response resources (DRRs) will play important roles in the capacity market auction. However, due to the uncertainty of outputs, they are not competitive enough in the market and face high investment risks. In order to deal with this situation, we integrate renewable energy resources (RESs), EVs and DRRs into a virtual power plant (VPP) and proposed a novel auction model for the VPP to participate in the capacity market. The objective function is to maximize the social welfare while satisfying the reliability of the system. This paper also presents the results of a case study with three scenarios to prove the validity. The proposed model provides a novel path for distributed flexible resources to participate in capacity market.

Keywords: Capacity market, electrical vehicle (EV), demand response resource (DRR), virtual power plant (VPP)

1. Introduction
In the power system, although the period of peak load is generally short, it is still necessary to establish a capacity market to stabilize the income of power generators and stimulate investment in power capacity, thereby achieving the target of ensuring short-term system safety and stability and ensuring long-term power supply adequacy [1].

In recent years, with the large-scale development of intermittent renewable energy resources, the demand of power system for reliable capacity is increasing. Ref.[2] design a capacity mechanism compensate for the externalities of wind power developments. Moreover, there are a lot of researches about the methods of calculating the capacity value of RES [3, 4], most qualifying capacity are calculated based on their historical output data. However, risks cannot be managed effectively by this method.

Except for power generation capacity, load-side resources are also important to maintain the capacity adequacy. The most typical representative of the load-side resources are the DRRs. It is widely known that the DRRs can benefit the system in the energy market. More than that, DRRs can also play important roles in the capacity market. Therefore, research on how DRRs participate in the capacity market has gradually attracted more attention [5, 6]. Ref.[7] proposes a new methodological framework to assess the potential reliability value of DRRs in smart grids. Ref.[8] has explored the role of DRRs as an alternative solution to replace transmission upgrades based on PJM capacity market. Otherwise, driven by the various advantages of EVs, EVs have become more important for low-carbon economy. EVs can be used as flexible energy storage resources to participate in the capacity market and replace high-cost energy storage units. Many methods have been discussed to evaluate the capacity of EV [9, 10]. However, due to the uncertainty of traffic conditions, users’ behavior and electricity price, which have
increased the risk and difficulty for EVs to participate in market. Therefore, through the centralized management of EV aggregators, not only can scale effects be formed, but also the use space of EVs can be expanded. Moreover, The application of new technologies will also further promote the operation of EVs[11-13].

In summary, there are many related studies on designing a reasonable capacity market mechanism to incent multiple flexible resources to participate in the capacity market so as to ensure resources adequacy of power system. However, these studies are mainly based on price mechanism and market structure, and all the capacity resources participate in the market auction separately. This will cause them to take high price risks and competitive pressures in the capacity market auction. To solve this problem, we proposed an auction model for the VPP to participate in capacity market by integrating RESs, EVs and DRRs. In fact, these resources have complementary characteristics, they can maximize utility and share risks with each other by combining to a VPP.

The main contribution of this paper are threefold:

- A VPP structure with RESs, EVs and DRRs is formulated. Otherwise, the procedures of information interaction and power flow within VPP are demonstrated clearly.
- A method for calculating the qualifying capacity of VPP is proposed.
- An novel capacity market auction model is proposed. The validity is verified via a test case.

The remaining of the paper is organized as follows. section 2 introduce the problem formulation. Section 3 describes the proposed auction model including the market optimization objective and constraints. In section 3, some cases are presented to demonstrate the validity of the proposed auction. Finally, a conclusion is given.

2. Problem formulation

The VPP model proposed in this paper is shown in the figure 1. The EV cluster, wind power, photovoltaic and DDRs form a VPP. Each part exchanges information with the VPP control center through modern communication technology. The VPP operation center integrates and analyzes the acquired data information to obtain the available bidding capacity of the VPP, and then participates in the capacity market. According to the bidding results in the capacity market, VPP will make the capacity resources ready to operate during the commitment period to ensure the power generation adequacy of the system. There will be penalties for those members who fail to perform accurately.

3. Capacity Market Auction Model

In this section, the capacity market auction model including conventional generators and VPP is described in detail. Similar to PJM, a slope demand curve for the capacity market is determined by ISO. The developed auction model can be executed for the whole jurisdiction or its zones separately. The model can also be implemented for the whole year or just peak periods of the year.

3.1. Capacity Auction Model Formulation

In this paper, we demonstrate the effectiveness of the proposed model through the social benefits generated by the capacity market auction. In an ideal capacity market, there will be an equilibrium point
for capacity demand and capacity supply as shown in (a) of figure 2. We divide the load demand into base demand and peak demand, corresponding to the horizontal section and sloped section of the demand curve. The shaded area represents the social welfare. Therefore, the objective of the developed bidding strategy is to maximize the social welfare.

$$\text{Maximize } \int_{0}^{\text{CAP}_d} F_d(CAP_d)d\text{CAP}_d - \int_{0}^{\text{CAP}_d} F_s(CAP_d)d\text{CAP}_d$$

(1)

Where $F_d(\bullet)$ and $F_s(\bullet)$ represent the demand function and supply function, respectively. $\text{CAP}_d$ represents the total requirement capacity. However, the supply curve is stair-stepping in the actual capacity market auction. Hence, according to Newton-Coates numerical method theory, we use a series of rectangular areas to approximate the value of the nonlinear integral, as shown in (b) of Fig.2.

![Figure 2. Supply and demand curves](image)

The new expression of the objective function is as fellow:

$$\overline{P^b} \cdot \text{CAP} + \sum_{i=1}^{N} \eta_i \cdot P^b_i \cdot \Delta \text{CAP} - \sum \mu_i \cdot \text{CAP}_r \cdot P^b_r \quad r \in \{\text{CG, VPP, IM, TU}\}$$

(2)

Where the $\overline{P^b}$ is the ceiling price of capacity offers and $P^b_i$ is the price of ith block in Fig.3(b). $\text{CAP}$ is the minimum value of the sloped demand curve. $P^b$ represents the auction price of technology r. $\mu_i$ is the bidding ratio and takes value from 0 to 1. $\eta_i$ is binary variable. $\Delta \text{CAP}$ is small increment. $\text{CAP}_r$ is the auction capacity of technology r. The first and second terms are a sum of demand sections. The third term represents the total bidding capacity supply from different technologies. It should be emphasized that we assume that the transmission upgrade plan is equivalent to a sort of generation capacity. Constraints (3) represent the sum of selected capacity offers that should be higher than the capacity requirement.

$$\sum \mu_i \cdot \text{CAP}_r \geq \text{CAP}_d \quad r \in \{\text{CG, VPP, IM, TU}\}$$

(3)

The high permeability of intermittent resources and varying load increases the system ramp requirement. Therefore, the capacity supply technology should be able to satisfy the maximum ramp requirement during the commitment period.

$$\sum \mu_i \cdot \text{CAP}_r \cdot \text{Ramp}_r \geq \text{CAP}_d \cdot \text{Ramp}_R \quad r \in \{\text{CG, VPP, IM, TU}\}$$

(4)

Where $\text{Ramp}_r$ represents the ramp ability of technology r. $\text{Ramp}_R$ is the ramp requirement coefficient of system. Since the capacity convert to energy supply when offers are carried out, the total actual energy supply ability of selected capacity should satisfy the load requirement, except the transmission upgrades. Constraint (5) represent the total load supply requirement of system to maintain the reliability of system. The total energy supply of selected generation offers can be calculated by (6). Constraint (7) control the supply higher than the requirement.
\[ E_r = \text{CAP}_r \cdot T_{CP} \cdot \sigma_{\text{load}} \quad (5) \]

\[ E_s = \sum \mu_r \text{CAP}_r \cdot T_{CP} \cdot \sigma_{\text{gen}} \quad r \in \{ \text{CG, VPP} \} \quad (6) \]

\[ E_s \leq E_r \quad (7) \]

Where \( E_r \) and \( E_s \) represent energy requirement and energy supply, respectively. \( T_{CP} \) is the commitment period. \( \sigma_{\text{gen}} \) is load factor of generators. The reliability of power system is described by loss of load probability (LOLP). It is important to fulfilled the system reliability requirement by constraints (8) and (9) according to [14].

\[ \text{LOLP} = \lambda_1 - \lambda_2 \cdot \sum \text{CAP}_r + \lambda_3 \cdot \text{CAP}_d \quad r \in \{ \text{CG, VPP, IN} \} \quad (8) \]

\[ \text{LOLP} \leq \text{LOLP}_{\text{MAX}} \quad (9) \]

Where \( \text{LOLP} \) represents the loss of load probability of selected capacities. \( \text{LOLP}_{\text{MAX}} \) is the maximum allowed generation system loss of load probability. \( \lambda_1, \lambda_2, \lambda_3 \) are constant coefficients. In order to prevent over-investment, market power management is needed in the capacity market. We mitigate market power by control the share of each generator within a reasonable range when participate in the capacity market. As shown in constraint (10).

\[ \sum \mu_r \text{CAP}_r \leq \lambda \text{CAP} \quad r \in \{ \text{CG, VPP, IN} \} \quad (10) \]

Where \( \text{CAP} \) is the maximum value of the sloped demand curve. \( \lambda \) represents a maximum percentage of demand that can be supplied by a capacity supplier. In order to ensure the supply capacity can be dispatched when needed, ISO set a series of rules to penalize members who are unable to delivery capacity reliably. Therefore, the reasonable compute of qualifying capacity is important for various power generation technologies to participate in the capacity market auction. For different generation technology characteristics, we calculate the corresponding confidence factor based on historical resource availability. For conventional generation, the confidence factor is calculated by constraint (11), where \( \varphi \) is the forced outage rate of generation units. The qualifying capacity of conventional generators is shown in constraint (12).

\[ \omega_{\text{CG}} = 1 - \varphi \quad (11) \]

\[ \text{CAP}_{r,\text{CG, INSTALL}} = \text{CAP}_{r,\text{CG, INSTALL}} \cdot \omega_{\text{CG}} \quad (12) \]

Where \( \varphi \) is the forced outage rate. \( \omega_{r} \) and \( \text{CAP}_{r,\text{INSTALL}} \) represent confidence factor and the install capacity of technology \( r \), respectively. According to [14], for centralized intermittent generation resources, the calculation method of confidence factors gets to be more complicated. The qualifying capacity is calculated based on the ratio of the rolling average of the actual power generation to the install capacity over the past three years.

\[ \text{CAP}_{r,\text{RES, INSTALL}} = \text{CAP}_{r,\text{RES, INSTALL}} \cdot \omega_{\text{RES}} \quad (13) \]

Despite the above approach, intermittent generation resources still face high investment risk caused by generation uncertainty in the capacity market. In addition to intermittent generation resources, EV clusters and DRRs are also facing the same situation. However, combine them into a VPP, it can not only mitigate the uncertainty by complementing the output, but also can spread risk. When calculating the confidence capacity, VPP needs to consider two factors: the capacity supply and the energy consumption during the delivery period. VPP required to consider satisfying the internal load demand first, then calculate the available capacity. Constraint (14) gives the total install capacity of VPP which include RES (e.g. Wind power and photovoltaic), EV cluster and DRRs. The confidence factor of VPP is defined in (15) as to calculate the qualifying capacity (16).
\[ \text{CAP}_{\text{VPP \_install}} = \text{CAP}_{\text{RES \_install}} + \text{CAP}_{\text{EV \_install}} + \text{CAP}_{\text{DR \_install}} \]  

(14)

\[ \alpha_{\text{VPP}} = \frac{\text{CAP}_{\text{RES}} + \text{CAP}_{\text{EV \_S}} + \text{CAP}_{\text{DR}} - \text{CAP}_{\text{EV \_D}} - \text{CAP}_{\text{USERS}}}{\text{CAP}_{\text{VPP \_install}} \cdot T_{CP}} \]  

(15)

\[ \text{CAP}_{\text{VPP}} = \text{CAP}_{\text{VPP \_install}} \cdot \alpha_{\text{VPP}} \]  

(16)

3.2. Revenue Distribution

Based on game theory, the model established in Section 3.1 can be considered as a collaborative game model among the entities within VPP. The purpose is to mitigate uncertainty and spread risk, thereby avoiding penalty and maximize the overall profit of VPP. It is necessary to make a reasonable distribution of profits so as to incent all entities and enhance their participation willingness. We adopt Shapley theory to distribute profit within VPP as described by (17) and (18).

\[ \chi_{i} = \sum_{S} \phi(|S|)[V(S) - V(S \setminus \{i\})] \]  

(17)

\[ \phi(|S|) = \frac{(M - |S|)!(|S| - 1)!}{M!} \]  

(18)

Where \( V(S) \) represents the cooperative profit of VPP, \( S \setminus \{i\} \) represents the set of all the entities except \( i \). \( \chi_{i} \) is the profit of \( i \)th entity and \( \phi(|S|) \) equals the weighting factor.

4. Case study

In this section, the effectiveness of the proposed capacity auction model will be verified by using a test data. The case study gives a sense of the expected results from the model.

4.1. Basic Data

A test data set was created to verify the proposed model. The values of parameters are shown in table 1. Other data of capacity resources are obtained from the actual market of PJM.

| Table 1. Basic Data |
|---------------------|
| \text{CAP} | \text{CAP} | \text{P} | \text{RAMP} | \text{RAMP \_ R} |
| 3000MW | 5000MW | 600$ | 0.1days | 0.6 |
| \lambda_{1} | \lambda_{1} | \lambda_{1} | \lambda | \sigma_{\text{px}} |
| 2E-6 | 1.8E-9 | 2.4E-9 | 0.5 | 0.8 |

4.2. Case Study with Different Scenarios

In order to evaluate the performance of the extracted model, we present three scenarios based on different participants in the capacity market.

Case 1: conventional generation capacity and external capacity participate in capacity market auction.

Case 2: except for conventional generation capacity and external capacity, there are also RES, EVs and DRRs to participate in capacity market auction.

Case 3: the difference compared to case 2 is that RES, EV cluster and DRR combine to form a VPP to participate in capacity market auction.

Table 2 shows the detailed results of cases. It can be seen that there is a minimum amount of required capacity in case 1. However, the cost to achieve system reliability is the highest of three cases. And accordingly, the amount of social welfare is the least. Specifically, there are same amount of capacity requirement in case 2 and case 3. However, the social welfare in case 3 is much more than case 2, but the cost is lower. It indicates that RES, EVs and DRRs participate in capacity market auction in the form of VPP has high economic efficiency.

| Table 2. Result of Three Scenarios |
|-----------------------------------|
| Case 1 | Case 2 | Case 3 |
| Required | 4580 | 4620 | 4620 |
| capacity (MW) | Social welfare ($) | Cost ($) |
|--------------|--------------------|----------|
|              | 1849515            | 524024   |
|              | 1891972            | 486368   |
|              | 1934573            | 443766   |

Figure 3 shows the detailed contributions from different participants in three cases. In case 1, the local capacity resources cannot fully meet system reliability requirements, therefore external capacity needs to be imported. However, this correspondingly increase the burden of the transmission network during the peak load period. Then, as can be seen from case 2, the entry of RES, EVs and DRRs can reduce the dependence on external capacity resources, but still cannot maximize the utility of local capacity resources, and there are only PV and DRRs participating in the capacity market successfully. As shown in case 3, all the RES, EVs and DRRs can be adopted in the capacity market auction by combining into VPP. Apparently, this further illustrates the validity of the proposed auction model.

4.3. Impacts of LOLP on the Proposed Model
LOLP is an important indicator for assessing the reliability of a power system. Reliability requirements are reduced as LOLP increases. It is necessary to analyze its impact on the auction model. Fig.4 illustrates the detailed impacts with the variation of LOLP. We can conclude that VPP can satisfy a wide range of reliability requirement. Only when the system reliability requirement level is extremely high, some generators with better performance than VPP are needed to provide capacity. It is reasonable that the capacity requirement and system cost decrease when LOLP increases, and there will be more social welfare.

![Figure 4 Variation of COST and SF with respect to maximum LOLP](image)

4.4. Impacts of Ramp Requirement of System on the Proposed Model
Due to the fast varying loads and intermittent generators, the system has ramp power requirements for the selected offers in the capacity markets. This means that lower prices may not necessarily dominate the capacity market auction. The impacts of ramp coefficient are shown in Fig.5. Since VPP is combined by RESs, EVs and DRRs, the flexibility and ramp ability are strong, it is hardly affected by the ramp...
coefficient. Conversely, the conventional generators get more affected. When the value of ramp coefficient is between 0.5 and 0.7, we can find that the corresponding results is the same. The reason for this result is that the ramp requirements in these cases are low and easily to satisfy, and the ramp constraints in the model can be ignored. However, with the increasing of ramp coefficient from 0.7, it is necessary to adopt capacity offers with better ramp ability. Meanwhile, the cost will increase and social welfare decrease.

5. Conclusion
This paper presents a capacity market auction model built for RESs, VEs and DRRs. It provides a novel path for distributed flexible resources to participate in capacity market. Based on a case study with three scenarios, the validity of the model is verified. Furthermore, we can conclude that RESs, EVs and DRRs participate in capacity market auction in the form of VPP can reduce the cost of maintaining system reliability and maximize their utility, and has high economic efficiency. This model helps to promote the construction and improvement of the capacity market mechanism in the future.

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7. References
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