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Risk-averse energy trading among peer-to-peer based virtual power plants: A stochastic game approach[☆]

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ABSTRACT

Developing clean and renewable energies provides a good solution to mitigate the growing environmental and energy crises, however, electricity market structures have not yet embraced the evolution to include these decentralized, small-scale and uncertain renewable generation units. In this paper, peer-to-peer based virtual power plants are proposed for risk-averse energy trading of small-scale generations and consumers. Inside the virtual power plants, peer-to-peer platforms are introduced to coordinate the small-scale generators and consumers into virtual power plants. The uncertainty of the renewable-based generations is compensated by the energy diversities in virtual power plants, which further improves the energy utilization efficiency of the renewable-based generations. Physical electricity trading approach is adopted, which promotes local electricity consumption and reduces the power congestion risk. For energy trading among virtual power plants, financial trading approaches (e.g.day-ahead contracts) are provided. The diversified trading framework of the proposed mechanism facilitates the renewable energy's access to the electricity market despite their small-scale and non-dispatchable characteristics. Moreover, a two-stage stochastic game model is proposed for the day-ahead energy bidding strategies, in which Cournot Nash pricing mechanism is introduced to balance the supply and demand and the conditional value-at-risk is employed for overbidding risk management. A set of realistic case studies of the Australian energy market and their analysis allow us to show that such a peer-to-peer-based virtual power plant market structure can effectively reduce the overbidding risk while maximizing the renewable energy usage.

1. Introduction

Recently, the human society is experiencing growing environmental crises due to the use of fossil energy, such as global warming, depletion of fossil energy and environmental pollution. Developing clean and renewable energies (e.g. solar PVs, wind farm) provides a good solution to these problems. However, electricity market structures have not yet embraced the evolution to include these decentralized, small-scale and uncertain renewable generation units. How to facilitate their access to electricity markets while balancing the risk of uncertain energy generation becomes an important subject. This requires profoundly rethinking electricity market design in a more compatible and risk-aware manner.

Integrating risk management techniques with the traditional energy market is one promising option to deploy a more risk-aware market entity. Various risk management techniques which are widely used in the electricity market are discussed in [1]. They are categorized into six main areas based on different risk management targets, which include marketers [2], resource planning [3], generation companies [4], power systems ([5–7]), power suppliers [8,9] and consumers [10]. In [11], the conditional value at risk method is employed, which deals with the generation risk of renewable energy from the perspective of a microgrid. Optimal scheduling strategy of the controllable resources is obtained to maximize the profit of a single microgrid, which ignores the cooperative effects among microgrids in the electricity market. To deal with the problem, in [12], conditional value-at-risk is used to measure the risks induced by uncertainty of renewable generations and loads, where risk management is designed for cooperative multiple coupled microgrids. These studies focus on the problem of the wholesale market. There are also works consider the risk management in the retail electricity market. In [13], conditional value at risk (CVaR) is used to quantify the low-profit risk and the volume deviation risk from the perspective of a retailer. In [14], CVaR is introduced as a risk measure method in a retail

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electricity market, which quantifies the uncertainty of pool prices and clients' demands. Considering the dynamic tariffs, in [15], CVaR is used to measure the risks of dynamic tariffs, uncertain spot price and regulating price from the perspective of a retailer. As important market participants, the power plants and the power consumers should also be taken into accounts. In [16], the mean–variance portfolio theory is used for risk management of a generation company. In [17], from the perspective of electric power and natural gas system, CVaR is employed for operating cost minimization within a certain risk range. In [18], the downside risk constraints are introduced to model the risks of the uncertain solar generation and electricity market price, where the risk management is accomplished from the perspective of the central concentrating solar power plant. In [19], conditional value-at-risk is used to manage the risks of volatile electricity spot market prices, where risk management is considered from the perspective of power consumers. These works considers the problem from the perspective of market participants (e.g., microgrids, the retailers, the power plants or the power consumers), which ignore the importance of risk management in a broader view. In [20], a probabilistic framework is proposed for risk measurement of supply shortfalls in the electricity market of Great Britain, where the risks are considered from the perspective of the electricity market to support the capacity mechanism design. Specifically, in [21], computable general equilibrium model is introduced to evaluate the risks of electricity market mechanisms and energy policies on the national economy. The model seeks to manage the risk of electricity market from the perspective of the resource planning.

Most of the existing works target on risk management of power systems, marketers and power suppliers. Only a small number of them focus on the risk management of generation companies, whose size is far bigger than the distributed generation units. Thus the existing electricity market is not compatible with the small-scale distributed renewable generation units, which contradicts with the deployment of renewable energy in the electricity market. Though these distributed renewable generation units have sufficient generations, once they cannot benefit from the electricity market, they tend to go off-grid. This is an unsatisfactory outcome, both from the perspective of generation units and the electricity market.

Note that the small-scale characteristic is one of the main reasons which inhibits the distributed generation units from participating in the electricity market, the concept of virtual power plants (VPPs) has been proposed in recent years as a collection of distributed energy resources [22]. In [23], the optimal energy trading within the VPP is achieved. However, the trading strategy is designed from the perspective of the power system. Consider from the perspective of the VPP, in [24], an energy management system is introduced, which achieves centralized minimization of VPP's total operating cost. From the perspectives of the prosumers, in [25], a superior prosumer with thermal units and interruptible loads is introduced for energy management of the inferior prosumers, which achieves the real-time optimal scheduling wit-hin the VPP. In [26], a centralised VPP model is introduced to make distributed energy resources competitive in the electricity market. To further improve the competitiveness of the intermittent renewables, in [27], a centralized VPP model is proposed for optimization of the internal power output. In all the aforementioned works about VPPs, the top-down structure does not allow for flexible energy trading within the VPP, thus cannot achieve coordination of decentralized distributed renewable generations, each with different owners and characteristics. This leads to a low energy utilization efficiency of the VPPs.

Recent years, peer-to-peer energy-trading platforms is proposed, which allows for the flexible energy trading among the peers with different preferences [28–30]. In [31], various peer-to-peer energy trading platforms which facilitate energy trading of different levels are introduced, from peer-to-peer within a microgrid, within a CELL (multimicrogrids) and among CELLs (Multi-CELLs). To coordinate the energy resources with different owner and preferences, in [32], bilateral contract networks are designed for peer-to-peer energy trading within an islanded microgrid, which incentivise coordination of large-scale and small-scale energy resources' owners. In [33], a peer-to-peer local community energy pool is proposed to enable the energy trading among local users with the aim of heterogeneous energy sharing within the community. In [34], the peer-to-peer trading mechanism is employed for local energy transaction within a community made up of heterogeneous dwellings. In [35], a peer-to-peer energy market platform within a community is proposed, which deals with energy trading between prosumers with heterogeneous preferences. In practice, the individual peers only consider their own interests, thus the whole energy trading process can be modelled as a game. Based on this idea, in [36,37], the peer-to-peer energy trading platforms are designed for energy trading within a microgrid and the trading mechanisms are simulated using game theory. In [38], peer-to-peer energy tradings within a community are modelled with various game models. The usage of game models can also benefit the market paradigms design. In [39], three representative market paradigms are designed for peer-to-peer energy trading within a community by the aid of game models. Even though the game models take the individual interests of the peers into accounts, without proper incentives, there will not be enough peers participating into the market.

From the aforementioned discussion, we can see that, on the one hand, coordinating the small-scale distributed renewable generation units (SDRG) into VPPs allows for an indirect risk management of the SDRG, thus can achieve integrating SDRG into the electricity market. On the other hand, the existing frameworks of VPP cannot achieve coordination of various distributed energy resources, each with different owners and characteristics, while the peer-to-peer platform provides a promising solution for this problem.

Thus here, a peer-to-peer based virtual power plant (VPP) is proposed for the risk-averse energy trading of small-scale generations and consumers. Inside the VPPs, the uncertainty of the renewable-based generations is compensated by the energy diversities. Moreover, a two-stage stochastic game model is proposed for the day-ahead energy bidding strategies, in which Cournot Nash pricing mechanism is introduced for the balance of load and demand. This further improves the energy utilization efficiency of the renewable-based generations. The contents of the remaining parts of this paper are summarized in Fig. 1. The major contributions are as follows.

1) A peer-to-peer based virtual power plant (VPP) is proposed for risk-averse energy trading of small-scale generations and consumers. Inside the VPPs, peer-to-peer platform is introduced to coordinate the small-scale generators and consumers into virtual power plants. Physical electricity trading approach is adopted, which promotes local electricity consumption and reduces the power congestion risk. For energy trading among VPPs, financial trading approaches (e.g. day-ahead contracts) are provided. The diversified trading framework of the proposed mechanism facilitates the renewable energy's access to the electricity market despite their small-scale and non-dispatchable characteristics.

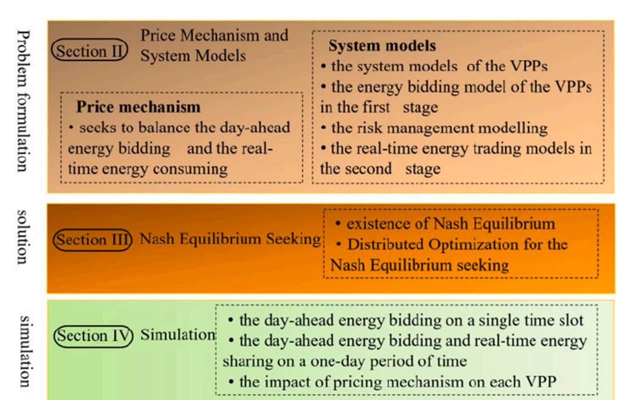


Fig. 1. Flowchart for the content structure.

2) A two-stage stochastic game model is proposed for the day-ahead energy bidding strategies of VPPs built on the peer-to-peer platform, where the trade-off between the overbidding risks and the energy utilization efficiency is considered.

3) The uncertainty of the renewable-based generations is compensated by the energy diversities in virtual power plants. Moreover, by introducing the Cournot Nash pricing mechanism, the energy utilization efficiency of the renewable-based generations has been greatly improved.

2. System model

In this section, we focus on the electricity market design for risk-averse energy trading of small-scale distributed renewable generation units (SDRG). As we can see from Fig. 2, the peer-to-peer based virtual power plant is proposed for coordination of the SDRGs, which further enables financial energy trading between VPPs and the main grid. Inside the VPP, the SDRGs and the consumers coordinates through the peer-to-peer platform to accomplish the day-ahead energy contracts with the main grid. Physical electricity tradings among the prosumers, which are managed by the distribution system operators, are adopted. For energy trading among VPPs, financial trading approaches (e.g.day-ahead contracts) are provided. Note that the price mechanism is a key part of the financial trading process, in the following, the price mechanism, which describes the financial energy trading between VPPs and the main grid, will be proposed first. Then the detailed modelling of energy trading inside VPPs will be introduced, as well as the risk management of VPPs.

2.1. Pricing mechanism

Given that the small-scale prosumers coordinated as VPP-s, whose impacts to the grid cannot be neglected, here we use a linear price function to deal with the inconsistency between the energy bidding and the forecasted power outputs, which are described as follows:

$$p_i^{DA,t} = p_i^{DA_0,t} - \frac{p_i^{DA_0,t}}{D_i^{DA_0,t}} q_i^{DA,t} \tag{1}$$

$$p_i^{w,t} = p_i^{w_0,t} - \frac{p_i^{w_0,t}}{D_i^{w_0,t}} \left(q_i^{w,t} + r_i^{w,t} \right) \tag{2}$$

where $p_i^{DA,t}$ is the day-ahead price, $D_i^{w_0,t}$ is the total demand parameter for the day-ahead pricing mechanism for VPP $i, q_i^{DA,t}$ is the day-ahead bidding quantity of VPP $i; p_i^{w,t}$ is the real-time price, $r_i^{w,t}$ is the energy injected at/taken from VPP $i, q_i^{w,t}$ is the real-time bidding quantity of VPP i, where the superscript w represents a uncertain scenario.

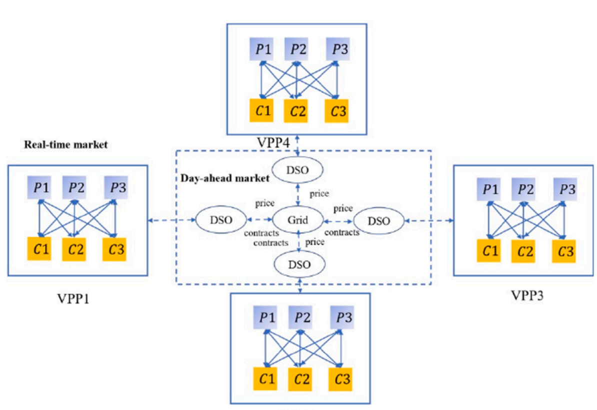


Fig. 2. The proposed market structure for peer-to-peer based VPPs.

2.2. Models inside VPPs

1) Renewable Energy based VPP: as we know, generation from a single type of renewable source will be correlated with weather conditions, thus are not stable. Note that energy diversity enables the stability of power production, we considered aggregated groups of multi-energy system here, which have significantly less variability if they are well-coordinated. This leads to the introduction of renewable energy based VPP. In Renewable Energy based VPP, muilti-class peer-to-peer energy trading allow small suppliers to compete with large traditional suppliers, which achieve the aim of aggregating prosumer DERs to provide stable upstream services to the main grid. Consider a renewable energy based VPP which is formed through the peer-to-peer energy trading architecture, where there is excess energy that can be sold, the quantity $q_i^{DA,t}$ of the energy bidding is determined by the utility maximum process.

It includes the renewable energy generation device (e.g. PV panel, wind turbine), residential prosumers which owns DERs and are willing to participate in the energy market. For renewable energy device, the daily operational cost C_{ij} is a constant that will not change with the energy output. For the main grid, the cost function can be formulated as follows:

$$C_{ig}\left(q_{ig}\right) = \gamma \left(q_{ig} - q_i^{DA,t}\right)^2, \tag{3}$$

where $q_{ig} < 0$ denotes the grid taken power, note that $q_{ig} > 0$ means power-in and $q_{ig} < 0$ means power-out here. For the prosumers which are not renewable based, the cost function of prosumer j in VPP i is composed of a production cost (or a personal satisfaction/convenience for electricity usage, and it can be expressed as a function of energy demand). Here we model the production cost and the consumer utility function as quadratic functions of the power set-point, which is described as follows:

$$C_{ij}\left(q_{ij}\right) = \frac{1}{2} a_{ij} q_{ij}^2 + b_{ij} q_{ij} + d_{ij}, \tag{4}$$

where a_{ij}, b_{ij} and d_{ij} are positive parameters. The total cost of VPP i can thus be described as

$$C_i = \sum_{j \in \Omega_{ic}} C_{ijm}\left(q_{ijm}\right) + \sum_{j \in \Omega_{ip}} C_{ijm} + C_{ig}\left(q_{ig}\right),$$

where Ω_{ic} is the set of consumers and Ω_{ip} is the set of producers. To model this trading scheme, the net power injection q_{ij} of prosumer j in VPP i can be split into a sum of bilaterally traded quantities with a set of neighboring agents $m \in w_{ij}$, i.e.,

$$q_{ij} = \sum_{m \in w_{ij}} q_{ijm}. \tag{5}$$

A positive value corresponds to a sale/production and a negative value to a purchase/consumption. The set $\{q_{ijm} \mid i \in \Omega, j \in \Phi, m \in w_{ij}\}$ is the set of decision variables. Different from the classic pool-based model, the equilibrium between production and the consumption is replace by a set of reciprocity constraints defined by all agents $j \in \Omega_i$ and $m \in w_{ij}$, which is described as follows:

$$q_{ijm} + q_{imj} = 0. \tag{6}$$

The power set-points of prosumer j in VPP i are constrained by the power boundaries $\underline{Q_{ij}}$ and $\overline{Q_{ij}}$. The role of each agent is restrained to either producer or consumer($\underline{Q_{ij}} \cdot \overline{Q_{ij}} \geqslant 0$). This can be modeled as the following constraints:

$$\underline{Q_{ij}} \leqslant q_{ij} \leqslant \overline{Q_{ij}}, \forall j \in \Omega_i. \tag{7}$$

$$q_{ijm} \geqslant 0, \forall (j,m) \in (\Omega_{ip}, m \in w_{ij}), \tag{8}$$

$$q_{ijm} \leq 0, \forall (j,m) \in (\Omega_{ic}, m \in w_{ij}), \tag{9}$$

2.3. First-stage model: energy bidding of VPP

Consider the revenue of VPP, the corresponding mathematical model for each VPP can be formulated as:

$$Maximize \quad profit = revennue - cost - risk. \tag{10}$$

Thus for VPP i, the corresponding utility function can be formulated as follows:

$$f_i\left(q_i^{DA,t}, q_i^{w,t}\right) = p_i^{DA,t} q_i^{DA,t} + E\left[p_i \Delta q_i^{w,t} - C_i\right. \tag{11}$$

$$\left. + S\left(q_i^{DA,t}, g_i^{w,t}\right)\right], \tag{12}$$

$$s.t.(6) - (9). \tag{13}$$

Note that for VPPs with different elementsčň the revenue functions are various. In the following, detailed modelling of various VPPs are given.

1) Fuel-based VPP: the fuel-based VPP includes traditional fuel-generation units, and the cost can be formulated as follows:

$$C_i = \frac{1}{2} a_i \left(q_i^w\right)^2 + b_i q_i^w + d_i, \tag{14}$$

where a_i, b_i and d_i are non-negative parameters which depends on the generation characteristics of traditional fuel-generation units. Then according to (10), the corresponding utility function can be formulated as follows:

$$\begin{aligned} f_i\left(q_i^{DA,t}, q_i^{w,t}\right) &= p_i^{DA,t} q_i^{DA,t} + E\left[p_i \Delta q_i^{w,t}\right. \\ &\quad \left. - \left(\frac{1}{2} a_i \left(q_i^w\right)^2 + b_i q_i^w + d_i\right)\right], \end{aligned} \tag{15}$$

2) DR-based VPP: for the DR-based smart building units, the cost function represent the willingness to compromise, thus the cost function can be formulated as follows:

$$C_i\left(q_i^{w,t}\right) = \mu\left(T_{in,i}^{w,t} - T_0\right)^2, \tag{16}$$

where $T_{in,i}^{w,t}$ is determined by the following energy-balance equation of the smart building:

$$T_{in,i}^{w,t} = T_{in,i}^{w,t-1} + \alpha\left(T_{in,i}^{w,t} - T_{in,i}^{w,t-1}\right) - \beta q_i. \tag{17}$$

Then using (10), we can obtain its utility function:

$$\begin{aligned} f_i\left(q_i^{DA,t}, q_i^{w,t}\right) &= p_i^{DA,t} q_i^{DA,t} + E\left[p_i \Delta q_i^{w,t}\right. \\ &\quad \left. - \left(\mu\left(T_{in,i}^{w,t} - T_0\right)^2\right)\right], \end{aligned} \tag{18}$$

3) VPP aggregator: Note that due to the uncertainty of the renewable-based generators, some VPPs may have a short supply, while others can produce more electricity in real-time than their bid, an aggregator is introduced, which take the excess energy to compensate the shortfall. However, this leads to additional management cost. With the aid of the linear price mechanism in section A, the management cost can be minimized under the condition that the generations of the renewable-based generators are uncertain by maximizing the social warefare of the aggregator, which is formulated as follows:

$$f_a\left(r_i^{w,t}\right) = \sum_{i=1}^{I} E\left\{ \int_0^{q_i^{w,t} + r_i^{w,t}} p_i^{w,t}\left(\tau\right) d\tau - C_i\left(q_i^{w,t}\right)\right\}, \tag{19}$$

where $r_i^{w,t}$ is the energy injected into VPP i and it should satisfy the energy balance constraints which are described as follows:

$$\begin{cases} \sum_{i=1}^{I} r_i^{w,t} = 0, & (a) \\ q_i^{w,t} + r_i^{w,t} \geqslant 0. & (b) \end{cases} \tag{20}$$

2.4. Risk management of VPPs

Note that VPPs make profits by selling electricity in the market, there is a tendency for them to bid more energy than they can produce. This leads to the overbidding problem in the VPP-based electricity market. Moreover, the uncertainty in the renewable generation and the local loads also aggravate the overbidding problem. From the perspective of electricity market, the risk management of overbidding is necessary. Here, the following CVaR measurement is introduced

$$\begin{aligned} & CVaR_{\theta_i}\left(X\left(Q_i^{w,t}, q_i^{DA,t}\right)\right) \\ &= argmin_{c_i \geqslant 0} c_i + \frac{E\left[X\left(Q_i^{w,t}, q_i^{DA,t}\right) - c_i\right]^+}{1 - \theta_i}, \end{aligned} \tag{21}$$

which can be relaxed as follows

$$\begin{aligned} & CVaR_{\theta_i}\left(X\left(Q_i^{w,t}, q_i^{DA,t}\right)\right) \\ &= argmin_{c_i, r_w}\left\{ c_i + \frac{\sum_{k=1}^{K} r_{w_k}}{K(1-\theta)} \right\} \end{aligned} \tag{22}$$

$$s.t. r_{w_k} \geqslant max\left\{0, q_i^{DA,t} - Q_i^{w,t}\right\} - c_i \tag{23}$$

$$r_w \geqslant 0 \tag{24}$$

$$c_i \geqslant 0 \tag{25}$$

Through risk-averse energy management, each VPP tries to maximize its revenue against the risk from the generation and load uncertainty. Therefore, the risk-averse energy bidding of VPP i can be realized by maximization of the following objective

$$\begin{aligned} F_i\left(x_i, x_q, w\right) = & \sum_{i=1}^{T}\left\{ f_i\left(q_i^{DA,t}, q_i^{w,t}\right)\right. \\ & \left. - \eta_i CVaR_{\theta_i}\left(X\left(Q_i^{w,t}, q_i^{DA,t}\right)\right)\right\}, \end{aligned} \tag{26}$$

where $x_i = [q_i^{DA,1}, q_i^{w,1}, c_i^1, q_i^{DA,2}, q_i^{w,2}, c_i^2, \ldots, q_i^{DA,T}, q_i^{w,T}, c_i^T]$. For the aggregator, considering that it can only control the power injected in/ taken from the VPPs, the energy management objective regarding it can be formulated as follows

$$\begin{aligned} & F_a(x_a, x_i, w) \\ &= \sum_{i=1}^{T} \sum_{i=1}^{N} E\left\{ \int_0^{q_i^{w,t} + r_i^{w,t}} p_i^{w,t}\left(\tau\right) d\tau - C_i\left(q_i^{w,t}\right)\right\} \end{aligned} \tag{27}$$

2.5. Second-stage model: real-time energy trading of VPP

After the first-stage energy bidding decisions are taken and the uncertain power generations of renewable energy generation becomes known, it is required to decide real-time energy trading in real-time market, they are the second-stage decisions under random uncertainty.

First, the random waste renewable generations at scenario w is represented as:

$$d_i^{w,t} = g_i^{w,t} - q_i^{DA,t}. \tag{28}$$

Assume that the generators each own ancillary plants, which maybe dispatched in forward and real-time market, so we do not consider energy pitfall here. As for the consumers, in first-stage, we have matched the forecast power with energy bidding and the consumers' demand which have time flexibility. Here, in the second-stage, we will match the uncertain renewable power generation with demand having power flexibility.

In spot market, the energy balance can be modeled as:

$$d_i^{w,t} = \sum_{j=1}^{N} q_{ij}^{Å!!}, \tag{29}$$

where $q_{ij}^{Å!!}$ is the energy trading quantity of consumer j in the second stage. Using the overproduced energy output, we need to maximize the consumers' social welfare, which is formulated as follows:

$$C2 = \sum_{j \in \Omega_c} C_j \left(q_{ij}^{'} \right) \tag{30}$$

Thus the second-stage optimization model can be modeled as the following problem:

$$minC2 \tag{31}$$

$$s.t.(29) \tag{32}$$

The optimal values of 31,32 is denoted as $S(q_i^{DA,t}, g_i^{w,t})$.

3. Nash equilibrium in a stochastic game and the distributed seeking algorithm

3.1. Nash equilibrium

In our proposed framework, peer-to-peer based VPPs participates bidding of the electricity market with uncertain renewable generations, thus they all tries to maximize their own profit which includes the energy overbidding risks of Section 2.4 in the stochastic environment. The whole decision problem of the first stage can be modeled as a stochastic game.

Let set $\Xi = \{1, 2, \ldots, N\}$ be the set of VPP players which participates in energy bidding in the electricity market. Each participants $i \in \Xi$ controls its bidding strategy $x_i \in \Omega_i$. $x_{-i} \in \Pi_{i \in \Xi \setminus i} \Omega_i$ denotes all players decision set except player i, and $x = (x_i, x_{-i}) \in \Pi_{i \in \Xi} \Omega_i$ represents all players decision set. Each VPP makes its bidding strategy to maximize it own profit with uncertain renewable generation,

$$max_{x_i \in \Omega_i} F_i(x_i, x_{-i}, w) \tag{33}$$

The aggregator tries to maximize it own benefit,

$$max_{x_a \in \Omega_i} F_a(x_a, x_{-a}, w) \tag{34}$$

Under this mathematical framework, the whole problem turn out to be seeking the Nash Equilibrium of the stochastic game. The corresponding Nash Equilibrium is a strategy profile on which no participant can benefit more by unilaterally changing its strategy. Note that the cost functions $C(\cdot)$ and the risk management function $CVaR_\theta(\cdot)$ are concave respect to x, while the revenue function for each VPP are convex respect to x, we can obtain that the profit $F_i(x_i, x_{-i}, w)$ is concave respect to x. This guarantees the existence of the Nash Equilibrium of the aforementioned game.

In this section, a distributed seeking algorithm is proposed for the bidding decision making of each VPP. Firstly, the NI function which defines the error metrics criteria is proposed,

$$\begin{aligned} &\varphi(x, y) \\ &= \sum_{i=1}^{I+1} \left[F_i \left(x_i, x_{-i} \right) \right) - F_i \left(y_i, x_{-i} \right) \Bigg) + \frac{\rho}{2} \Big\| x_i - y_i \|^2 \end{aligned} \tag{35}$$

by this definition, we introduce a best response dynamics based optimization framework to solve the problem. By taking the Lagrange function of the problem, we have

$$\begin{aligned} L(y, \lambda) = &\sum_{i=1}^{I+1} \left[-F_i^K \left(y_i, x_{-i} \right) \right) + \frac{\rho}{2} \Big\| x_i - y_i \|^2 \Bigg] \\ &+ \sum_{t=1}^{T} \sum_{i=1}^{I} \lambda_{i,t} \left(-q_i^{w_n,t} - r_i^{w_n,t} \right) \\ &+ \frac{\xi}{2} \cdot \sum_{t=1}^{T} \sum_{i=1}^{I} \lambda_{i,t} (-q_i^{w_n,t} - r_i^{w_n,t})^2 \end{aligned} \tag{36}$$

we redefine $x = [x_1, x_2, \ldots, x_N]$. The Lagrange function can be rewritten as:

$$\begin{aligned} L\left(y, y_a, \lambda \right) = &\sum_{i=1}^{I} \left[-F_i^K \left(y_i, x_{-i} \right) \right) + \frac{\rho}{2} \Big\| x_i - y_i \|^2 \Bigg] \\ &-F_i^a \left(y_a, x_{-a} \right) \Big) + \frac{\rho}{2} \Big\| x_a - y_a \|^2 \\ &+ \sum_{t=1}^{T} \sum_{i=1}^{I} \lambda_{i,t} \left(-q_i^{w_n,t} - r_i^{w_n,t} \right) \\ &+ \frac{\xi}{2} \cdot \sum_{t=1}^{T} \sum_{i=1}^{I} \lambda_{i,t} (-q_i^{w_n,t} - r_i^{w_n,t})^2 \end{aligned} \tag{37}$$

3.2. Distributed optimization for nash equilibrium seeking

An fast ADMM framework is proposed in Algorithm 1, where the Nash Equilibrium seeking is achieved.

Algorithm 1. distributed optimization for SAA NE seeking.

procedure Accelerated ADMM framework
  for each VPP's strategy x_k **do**
    initialize the strategy y_k;
  end
  k = 1;
  Randomly initialize $\lambda_k \in R_+^{KT}$;
  initialize $\tau_1 = 1$;
  initialize the strategy y_a;
  repeat
    y-update: all VPPs $i \in I$'s best strategies are solved by:

$$y_i \left(k+1 \right) \in argmin_{y_i \in \Omega_i} L\left(y_i, y_a \left(k \right), \bar{\lambda} \left(k \right) \right); \tag{38}$$

    y_a-update: the best strategy of the aggregator are solved by:

$$y_a \left(k+1 \right) \in argmin_{y_a \in \Omega_a} L\left(y \left(k+1 \right), y_a, \bar{\lambda} \left(k \right) \right); \tag{39}$$

    λ-update: the dual variables λ are updated by:

$$\lambda_{i,t}(k+1) = \left[\lambda_{i,t}(k) + \varepsilon \left(-q_i^{w_n,t} - r_i^{w_n,t} \right) \right]^+; \tag{40}$$

    The dual-acceleration step:

$$\iota_{i+1} = \frac{1 + \sqrt{1 + 4\iota_i^2}}{2}; \tag{41}$$

$$\begin{aligned} \bar{\lambda}_{i,t} \left(k+1 \right) = \lambda_{i,t} \left(k+1 \right) + \frac{\iota_i - 1}{\iota_{i+1}} \\ \cdot \left(\lambda_{i,t}(k+1) - \lambda_{i,t}(k) \right); \end{aligned} \tag{42}$$

    update $i = i + 1$;
    until $\|\lambda(k+1) - \lambda(k)\| \leqslant \varsigma$
    Return y_i and y_a.
    $q_{ij}^{'}$-update:

$$q_{ij}^{'} \in argmin_{\Omega_c} C_j \left(q_{ij}^{'} \right). \tag{43}$$

end procedure

4. Simulation

In this section, two realistic case studies will be given to illustrate the effectiveness of the proposed market structure.

4.1. Day-ahead energy bidding on a single time slot

To clearly show the energy usage improvement and bidding risks of the peer-to-peer based VPP, energy bidding and sharing of one renewable-based, one CHP-based, one DR-based VPPs is tested over the proposed framework on a single time slot. Here we consider the solar-based, solar and wind-based VPP, respectively. Choose the time slot $t = 132$ as the forward market and the time slot $t = 133$ as the spot market. As we can see from Fig. 3, with a single solar generation unit, the energy bidding without VPP framework is smaller than 400 kwh, while it is largely improved by coordination of the peer-to-peer energy trading in the VPP. Thus the energy utilization efficiency of the renewable-based generations has been greatly improved. To further illustrate the energy diversity effects, we also consider a solar and wind based VPP. As it can be seen from Figs. 4 and 5, the renewable energy usage can be divided as two parts, the energy bidding with the main grid and local energy trading through the peer-to-peer platform. With the diversified renewable generation, the uncertainty of the renewable generation is reduced from a certain degree. Moreover, with proactive consumers participating the peer-to-peer platform, the energy bidding to the main grid can be improved.

As we can see in Fig. 6, with local consumption being introduced, the upstream energy transmission with the main grid is largely reduced, which means the proposed framework increases the stability of the main grid by removing the cross-area power trades.

4.2. Day-ahead energy bidding and real-time energy sharing on a one-day period

In this section, the effects introduced by the proposed energy bidding and sharing strategy is evaluated on a DA energy bidding and real-time energy sharing problem. We consider the energy bidding of one solar and wind based, one CHP-based, one DR-based VPPs, where the solar and wind based VPP is formulated by coordinating 6 generators and 5 consumers through the peer-to-peer platform. The main grid is considered as a consumer node of the solar and wind based VPP. Note that five-minute bidding/dispatch settlement would provide a better price signal for the participants, the AEMC have made a final determination to alter the settlement period for the wholesale electricity spot market from 30 min to five minutes. Here, the DA energy bidding is build on 288 time slots, i.e., $T = 288$ and $\Delta T = 5min$. The renewable generation data published by AEMO from December 1, 2019 to December 30, 2019 is used. Flexible load and cost parameter datas of the consumers are from [40]. For pricing parameters in (1) and (2), $(p_i^{DA_0,t}, D_i^{DA_0,t})$, $(p_i^{w_0,t}, D_i^{w_0,t})$ are chosen as $(3, 8000)$, where $D_i^{DA_0,t}$ and $D_i^{w_0,t}$ are sufficiently large which guarantees that VPPs' bidding are not restricted by these parameters. In Fig. 7, the energy bidding and sharing results of the solar and wind based VPP is given, from which we can see that the overbidding rarely happen in the DA market. With the proactive peers participating in the energy sharing process, the non-bidding and uncertain renewable power

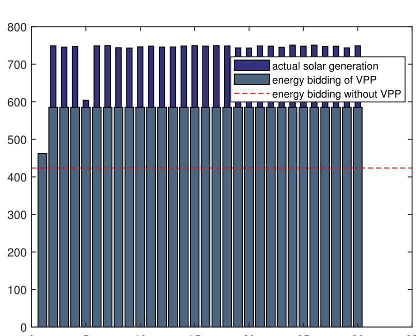


Fig. 3. Risk-averse bidding of solar-based VPP. .

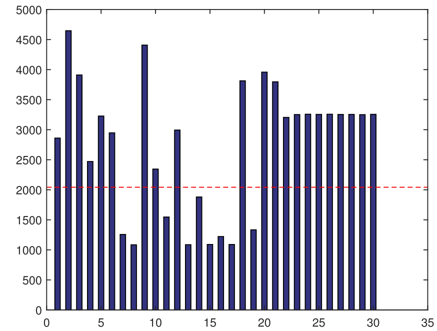


Fig. 4. Risk-averse bidding of solar and wind-based VPP.

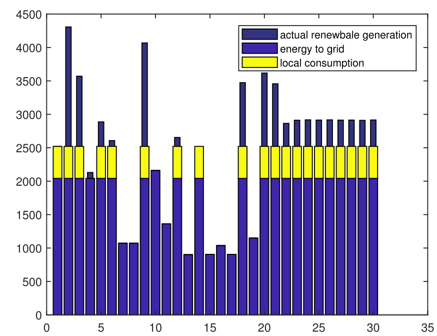
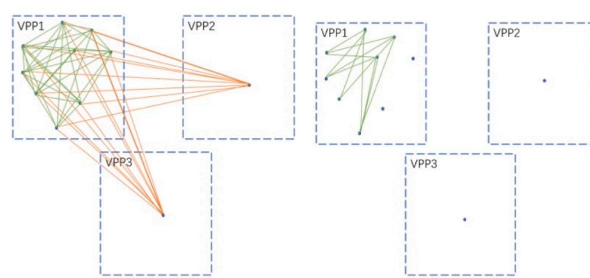


Fig. 5. Energy usage of solar and wind-based VPP.



(a) Power trades without VPP. (b) Power trades of VPP.

Fig. 6. Power trades of traditional and the proposed framework.

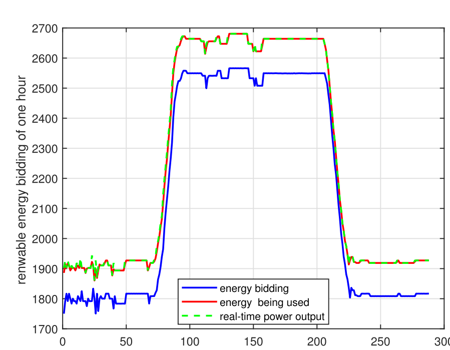


Fig. 7. Matching results of solar and wind based VPP.

outputs can be fully adopted by the peers, while keeping the overbidding risks at a low level.

In summary, using the proposed two-stage peer-to-peer based VPP framework, in the DA market, the forecast power is matched with the energy bidding and demand which have time flexibility. In real-time market, the unforeseen renewable power output is matched with demand having power flexibility. Thus the renewable generation is fully used while keeping the overbidding risks at a low level.

4.3. Impact of pricing mechanism on each VPP

In this section, we focus on the impact of pricing mechanism of the bidding strategy of each VPP. To clearly show the impact, here we choose three kinds of VPPs, one renewable-based, one fuel-based and one DR-based, their bidding potential is explored, as well as the internal relationship between the bidding quantity and the profit. We start by exploring their bidding potentials.

Let $p^{DA} = 3$. By choosing the demand parameter $D_i^{DA_0}$ on $[100, 2400]$, the tendency of the optimal bidding strategy with increasing demand parameter $D_i^{DA_0}$ can be obtained, which is shown in Fig. 8. As we can see from Fig. 8, the optimal bidding quantity of the renewable-based VPP is increasing with $D_i^{DA_0}$ on $[500, 1500]$, and it reaches its maximum when $D_i^{DA_0} = 1600$. As for the fuel-based and the DR-based VPP, it also gets saturated when $D_i^{DA_0} = 1600$. Due to its low marginal cost, the renewable-based VPP shows grear potential on the energy bidding market with the fuel-based and DR-based VPP. This means by coordinating the renewable DERs and small consumers to formulate the VPP, the proposed peer-to-peer VPP based framework shows competitive potential, which further guarantees the participation of the small DERs in the electricity market.

Let $p^{DA} = 3$ and $D_i^{DA_0} = 1600$, by changing the bidding quantity from 40 to 960, we can obtain relationship between the profit and the bidding quantity, which is shown in Fig. 9. The profit increases with bidding quantity when it is smaller than 840 and then decrease. As we can see, the VPPs try to make profits by bidding more, while the Cournot price mechanism leads to a decrease of the selling price when the bidding quantity gets large. Thus the VPPs cannot gain more profits by just bidding more. Their bidding is revised by the demands of the main grid, which is contained in demand parameter $D_i^{DA_0}$.

4.4. Comparison with the centralized VPP model

In this section, the influence of the peer-to-peer based VPP model on the energy utilization efficiency improvement is verified by comparison with the existing centralized VPP model in [27]. Let E_u be the energy being used, which includes the bidding electricity in the DA market and the local energy consumption in real-time peer-to-peer market. Let E_g be the total generated electricity of the VPP. Define the energy utilization efficiency η as $\eta = \frac{E_u}{E_g}$. To make a fair comparison, the same bidding structure and Nash-seeking algorithm are chosen, based on which the energy utilization efficiency of the the peer-to-peer based VPP and the centralized VPP is compared. Here we randomly choose eight typical scenarios (case 1–8) by using the real historical data from the Australian energy market. The results are presented in Table 1. It can be found that in all cases, the energy utilization efficiency of the peer-to-peer based VPP is higher than that of the centralized VPP. The energy utilization efficiency of the peer-to-peer based VPP can reach 99.127%, which is attributed to the peer-to-peer based VPP structure.

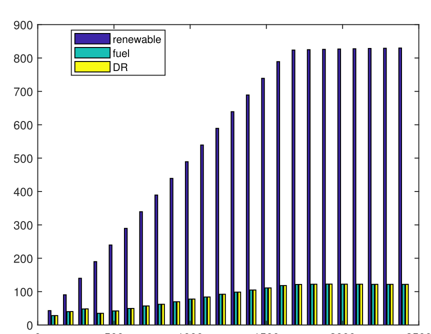


Fig. 8. The optimal bidding strategy with increasing the demand parameter D^{DA_0}.

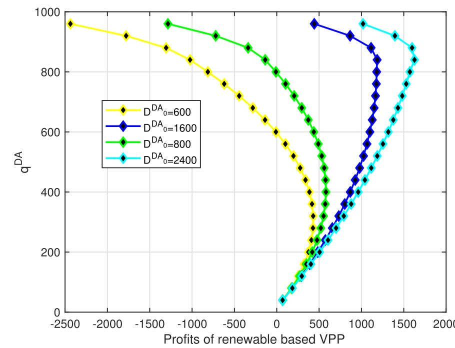


Fig. 9. The profit of renewable-based VPP with different bidding quantity.

5. Conclusion

In this paper, peer-to-peer based virtual power plants have been proposed for risk-averse energy trading of small-scale generations and consumers, where diversified energy trading mechanism is employed within and among the VPPs. The uncertainty of the renewable-based generations is compensated by the energy diversities in virtual power plants, and the diversified trading framework has facilitated the renewable energy's access to the electricity market despite their small-scale and non-dispatchable characteristics. Moreover, a two-stage stochastic game model has been proposed for seeking the optimal trading strategy of the proposed framework. Simulations based on the Australian energy market has shown that such the proposed framework can effectively reduce the overbidding risk while maximizing the renewable energy usage.

CRediT authorship contribution statement

Wen-Ting Lin: Data curation, Formal analysis, Investigation, Writing - original draft. **Guo Chen:** Funding acquisition, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - review & editing. **Chaojie Li:** Conceptualization, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial

Table 1
The energy utilization efficiency of the peer-to-peer based and the centralized VPP models.

Energy utilization efficiency	VPP Model	
	Peer-to-peer	Centralized
Case 1	97.807%	92.017%
Case 2	98.700%	91.859%
Case 3	98.801%	90.186%
Case 4	99.127%	89.353%
Case 5	97.695%	88.946%
Case 6	98.276%	89.587%
Case 7	98.690%	90.918%
Case 8	98.701%	91.937%

interests or personal relationships that could have appeared to influence the work reported in this paper.

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