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Optimal joint demand and virtual bidding for a strategic retailer in the short-term electricity market

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ABSTRACT

This paper proposes a bilevel stochastic optimization model for generating the optimal joint demand and virtual bidding strategy for a strategic retailer in the short-term electricity market, where virtual bidding is used to improve the retailer's market power in the day-ahead (DA) electricity market. In the proposed model, virtual bidding can be used at multiple buses, which are not limited to the locations of the demands of the strategic retailer. In the bilevel stochastic optimization model, the upper level problem maximizes the total profit of demand and virtual bidding, while the lower level problem represents the DA electricity market clearing process; the uncertain demands of the strategic retailer and real-time (RT) electricity prices in the market are represented by scenarios; and the Conditional Value at Risk (CVaR) is used for risk management. By using the duality theory, Karush–Kuhn–Tucker (KKT) conditions and big M method, the proposed bilevel nonlinear optimization model is converted into a single-level mixed-integer linear programming (MILP) problem, which can be solved efficiently by existing commercial solvers. Case studies are performed to validate the proposed model and study the impacts of various model parameters on the strategic retailer's joint demand and virtual bidding strategy.

1. Introduction

In the deregulated electricity markets, since most consumers do not have the expertise on power trading, they may prefer to sign long-term or mid-term bilateral contracts with the retailers to satisfy their power demand. In this circumstance, the retailers act as the intermediaries between consumers and electricity markets [1]. To manage the risk and lower the energy procurement cost, the retailers would expect to develop optimal demand side bidding strategies in which the uncertainties could be handled by using the stochastic [2] or robust optimization [3] technique. Since many retailers only have small shares in the electricity markets, they can be treated as price-takers whose behavior would have little influence on the electricity prices in the market [2–9]. However, if there is one or multiple dominant retailers in the market whose bidding strategies can affect the market outcomes significantly, they should be modeled as price-makers [10–16].

In the existing literature, the optimal demand side bidding strategies consider different market frameworks and physical assets to improve the demand side participants' economic benefits [2–16]. In [2], the retailers could participate in the future and spot markets simultaneously to manage the uncertainties, where the competition of rival retailers was also considered in the stochastic optimization model. The authors of [7] proposed a new trading mechanism for short-term demand response (DR) through which the retailer can receive short-term DR offer curves submitted by the customers to avoid unfavorable RT prices in the wholesale electricity markets. In [10], the retailers could adjust their DA bidding strategies based on the latest forecast results in several intraday markets in Spain, which are cleared after the DA market. In [3, 12] and [13], the time-of-use rate, time-shiftable, and coupon-based demand response programs were considered in the demand bidding strategies, respectively. In [5], the financial impact of demand response was quantified for the retailer. In [11], energy storage was used by a strategic load serving entity to lower the energy procurement cost through optimal charging and discharging strategies. The authors of [14] compared three types of price elasticity of the demand to show the benefits of using demand response. In [15] and [16], optimal demand side bidding strategies were proposed for strategic large consumers in electricity markets, and the impact of demand bidding on wind power integration was investigated in [16].

Even though there is abundant literature on developing demand side bidding strategies, a pure financial instrument called virtual bidding, which is designed based on the two-settlement structure of the US electricity markets, has not been considered yet. Virtual bidding is trading power in the DA and RT markets without generating or consuming it, and the profit of virtual bidding depends on the price differences between DA and RT markets. Virtual bidding is different from

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Nomenclature

Indices and Sets

- i Index of the demands owned by the strategic retailer, $i \in \{1, \cdots, I\}$.
- v Index of the virtual units owned by the strategic retailer, $v \in \{1, \cdots, V\}$.
- j Index of the generating units, $j \in \{1, \cdots, J\}$.
- l Index of demands owned by other retailers or consumers, $l \in \{1, \cdots, L\}$.
- t Index of time periods, $t \in \{1, \cdots, T\}$.
- w Index of scenarios, $w \in \{1, \cdots, \Omega\}$.
- b Index of demand blocks of the strategic retailer, $b \in \{1, \cdots, B\}$.
- q Index of energy blocks of a generating unit, $q \in \{1, \cdots, Q\}$.
- e Index of demand blocks of other retailers or consumers $e \in \{1, \cdots, E\}$.
- n Index of system buses, $n \in \{1, \cdots, N\}$.
- k Index of transmission lines, $k \in \{1, \cdots, K\}$.
- $r(k)$ Receiving-end bus of the transmission line k.
- $s(k)$ Sending-end bus of the transmission line k.
- ψ_n^I Set of the demands owned by the strategic retailer located at Bus n.
- ψ_n^V Set of the virtual units located at Bus n.
- ψ_n^J Set of the generating units located at Bus n.
- ψ_n^L Set of the demands owned by other retailers or consumers located at Bus n.
- ϕ_n Set of the buses connected to Bus n

Decision variables

- λ_{bit}^{SD} Bid price of block b of the demand i owned by the strategic retailer in a period t in the day-ahead (DA) market.
- D_{bit}^{SDmax} Maximum power of block b of the demand i owned by the strategic retailer in a period t in the DA market.
- D_{bit}^{SD} Cleared power of block b of the demand i owned by the strategic retailer in a period t in the DA market.
- P_{vt}^{VImax} Maximum incremental bid capacity of the virtual unit v in a time period t in the DA market.
- P_{vt}^{VDmax} Maximum decremental bid capacity of the virtual unit v in a time period t in the DA market.
- λ_{vt}^{VD} Bid price of the virtual unit v in a period t in the DA market when a decremental bid is used.
- z_{vt} Binary variable for the virtual unit v in a time period t, which is equal to 1 if an incremental bid is generated and 0 if a decremental bid is generated.
- λ_{vt}^{VI} Bid price of the virtual unit v in a period t in the DA market when an incremental bid is used.
- λ_{vt}^{VD} Bid price of the virtual unit v in a period t in the DA market when a decremental bid is used.
- P_{vt}^{VD} Cleared power of the virtual unit v in a period t in the DA market when a decremental bid is used.
- P_{vt}^{VI} Cleared power of the virtual unit v in a period t in the DA market when an incremental bid is used.
- P_{qjt}^{CD} Cleared Power of the block q of the generating unit j in a period t in the DA market.
- D_{elt}^{OD} Cleared power of the block e of the demand l of other retailers or consumers in a period t in the DA market.
- λ_{nt}^{DA} DA locational marginal price (LMP) at Bus n in a period t.
- f_{kt}^{D} Power flow of the transmission line k in a period t in the DA market.
- δ_{nt}^{DA} Voltage angle of Bus n in a period t in the DA market.
- ζ Auxiliary variable used to compute the Conditional Value at Risk (CVaR).
- η_w Auxiliary variable used to compute the CVaR in Scenario w.

Parameters

- D_{itw}^{SR} Actual demand i of the strategic retailer in the real-time (RT) market in a period t in Scenario w.
- λ_{ntw}^{RT} RT LMP at Bus n in a period t in Scenario w.
- P^{Vmax} Maximum total capacity of the virtual units in the DA market.
- D_{it}^{SF} Forecasted demand i of the strategic retailer in a period t in the RT market.
- P_{qjt}^{CDmax} Maximum power of the block q of the generating unit J in a period t in the DA market.
- $D_{elt}^{OD\max}$ Maximum power of the block e of the demand l of other retailers or consumers in a period t in the DA market.
- λ_{qjtw}^{CD} Offer price of the block q of the generating unit J in a period t in the DA market in Scenario w.
- λ_{elt}^{OD} Bid price of the block e of the demand l of other retailers or consumers in a period t in the DA market.
- π_w Probability of occurrence of a scenario w.
- B_k Imaginary part of the admittance of the line k.
- C_k^{max} Transmission capacity of the line k.
- λ^{CapD} Bid price cap of the DA market.
- β Risk aversion parameter of the strategic retailer.
- α CVaR per-unit confidence level.

generation or demand bidding of electricity market participants because it is not associated with any physical assets in the power grid. In the DA market, a virtual bidder may either buy or sell power based on its credit in the trading account, and all of its DA virtual power commitments should be zero out in the RT market, because the virtual bidder does not have any actual generation or demand sources. In contrast, a retailer with demand bidding needs to purchase power in the DA markets based on the consumers' electricity consumptions, and a power producer with generating bidding should sell power in the DA market, which is limited by its installed generation capacity. In this circumstance, the demand side participants in the electricity market, such as the retailer, can use virtual bidding to improve their economic benefits and decrease risks in the market without using additional physical assets.

Virtual bidding was first adopted by the PJM electricity market in 2000 [11]. In 2013, the cleared virtual bids of the five major U.S. wholesale electricity markets accounted for 13% of the total electric demand [17]. The authors of [18] addressed the main advantages and disadvantages of virtual bidding, and the impacts of virtual bidding on the electricity market operation were studied by many researchers in the academia and industry. The study of perfect virtual bidding in the market clearing processes in [19] and [20] showed that virtual bidding could improve market performance. Since virtual bidding was not introduced to California and New York electricity markets from the beginning, the authors of [21] and [22] could analyze the historical data with and without virtual bidding, and the studies showed that virtual bidding reduced price differences and increased market efficiency. However, some literature also pointed out that virtual bidding might not increase market efficiency in some conditions [23–28]. In [23], it was shown that a virtual bidder might not improve electricity market efficiency even though the virtual bidding was profitable, which was caused by the complicated power system operation processes. In [24], it was shown that if virtual bidders could not forecast prices accurately, they might not increase the total social welfare of the electricity market and should be screened out by the market operators. The authors of [25] addressed that, when the power network was congested, the price differences may not be reduced by virtual bidding. The work [26] and [28] showed that if virtual bidding was used by financial transmission right (FTR) holders and cyber attackers, respectively, it would bring financial losses to the system. Moreover, the reference [27] reported that the FTR holders using uneconomic virtual bidding violated the Federal Energy Regulatory Commission's anti-manipulation rule and should pay penalties to the market.

Even though an incentive for allowing virtual bidding in the electricity market is to increase power trading liquidity and mitigate market power, currently, the overall virtual trading volume in the U.S. electricity market is still not high enough to make the market perfectly competitive, because the participants using virtual bidding are limited by their credits, forecast capability, and risk tolerance. Even though virtual bidding is not related to any physical assets, the quantities of virtual bids are limited by the credit in the trading account. In this circumstance, the large firms with high credits can have more market power than the small firms with low credits in the DA market. Thus, the virtual bidding used by small firms cannot mitigate the market power. Moreover, since electricity price is usually much more volatile than the prices of other commodities, such as petroleum, natural gas, financial assets, metals, and agricultural products [29], the electricity price forecasts used for virtual bidding may not be accurate enough, leading to high potential risks for the electricity market participants using virtual bidding. Since most firms are risk-averse, they would be more interested in participating in other less-risky commodity markets instead of the electricity market. Thus, the virtual trading volume is much lower than the total demand in the U.S. electricity market. Furthermore, when the transmission line(s) connected to a bus are congested, even a small generation offer or demand bid can affect the electricity price at the bus significantly. Therefore, when transmission congestion occurs, a price-maker participant can use virtual bidding at the buses with the electricity prices sensitive to virtual bids to further increase its market power in the network-constrained electricity market.

In the existing literature, the virtual bidder was usually a pure financial entity [17–25], an FTR holder [26,27], or a system attacker [28]. However, the participants that own physical assets on the demand side, such as retailers or consumers, or the supply side of the power grid can also use virtual bidding to improve their profits and manage risks, and these participants are referred to as physical participants [26]. Based on the annual reports of PJM [30], in 2016 and 2017, about 63.5% and 55.2% of the cleared virtual bids in the PJM electricity market were from physical participants, respectively. In this circumstance, there is a need to develop efficient decision-making models for physical participants, such as a strategic retailer using virtual bidding while considering the uncertainties and risks in the network-constrained electricity markets. Therefore, this paper proposes a risk-constrained stochastic optimization model for generating the optimal joint demand and virtual bidding strategies for a strategic retailer while considering the impact of power congestion on the network-constrained market clearing. The main contributions of this paper are the following:

1) A bilevel stochastic optimization model for generating the joint demand and virtual bidding strategy is proposed for the first time. The market power of a strategic retailer in the DA market is increased by submitting incremental or decremental virtual bids at multiple buses in the power system, which can be different from the locations of the retailer's demands. The optimal joint demand power and virtual bidding strategies are generated simultaneously considering the retailer's risk preference.
2) This is the first work of studying the virtual bidding used by a demand side participant, i.e., a strategic retailer. The impacts of different maximum virtual bidding capacities, load levels, risk aversion parameters, and other participants' bidding strategies on the profitability of the strategic retailer are studied to further understand this type of virtual bidding used by demand side participants.

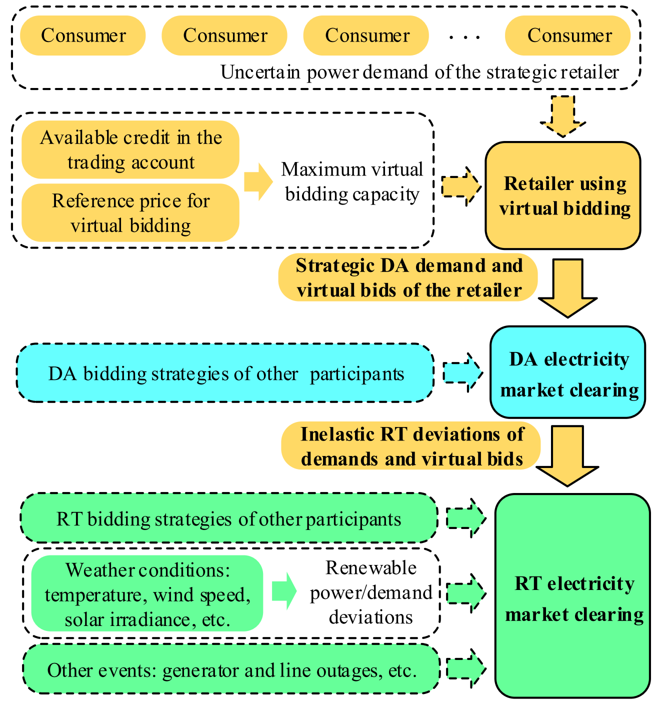


Fig. 1. Market structure for the strategic retailer using virtual bidding.

The remainder of this paper is organized as follows. Section 2 presents the problem description. Section 3 presents the model for generating the optimal joint demand and virtual bidding strategy for the strategic retailer. Section 4 demonstrates the effectiveness of the proposed model via case studies. Section 5 concludes the paper.

2. Problem description

2.1. Market framework

This paper addresses the short-term bidding problem of a strategic retailer in a two-settlement electricity market, which is shown in Fig. 1. On one hand, the retailer signs long-term or mid-term contracts with consumers and purchases power from the electricity markets. On the other hand, the retailer uses additional financial deposit as the credit to perform virtual bidding, which helps it earn more profit and manage risks.

The two-settlement electricity market usually has two trading floors: DA and RT markets. In the DA market, all the demands and virtual bids of the strategic retailer are cleared at DA prices through the DA market clearing process, which considers the offers and bids of all market participants. The total quantity of DA virtual bids should not exceed the maximum virtual bidding capacity, which is equal to the retailer's available credit divided by the reference price for virtual bidding. The credit of the retailer is equal to its financial deposit in the trading account, and the reference price for virtual bidding is specified by the market operator based on the historical electricity price data and is publicly available to all market participants. In the RT market, the demand and virtual deviations of the strategic retailer are settled at RT prices. Since the DA virtual bids were not based on actual generation or demands in the power system, the strategic retailer's RT virtual deviations are equal to its DA cleared virtual quantities, which are deterministic after the DA market clearing process. However, the strategic retailer's RT demand deviations are uncertain and affected by the RT behaviours of the end-use electricity consumers.

2.2. Bilevel stochastic programming structure

The structure of the proposed bilevel stochastic optimization model is depicted in Fig. 2. The uncertain parameters faced by the retailer are represented by scenarios and the expected total profit of the demand and virtual bidding of the retailer in the two-settlement electricity market is maximized in the upper level problem. The DA market clearing processes are modelled in the lower level problem, and the total social welfare is maximized while considering the impacts of the strategic retailer's demand and virtual bids on the DA prices. In this paper, the strategic retailer is modeled as a price-maker in the DA market, because it can submit the demand and virtual bids strategically to affect the DA prices for maximizing its expected profits. Specifically, the retailer has the flexibility to set the prices and quantities of the DA demand bids, as well as the locations, types, quantities, and prices of the DA virtual bids. In contrast, the RT power deviations of the retailer are inelastic and have to be settled at the RT prices automatically, which indicates that the retailer does not have the flexibility to behave strategically in the RT trading floor. Therefore, the retailer's market power in the RT market is much weaker than that of other participants with flexible resources, and the retailer is modeled as a price-taker in the RT market in the proposed model.

In the stochastic model depicted in Fig. 2, three types of uncertainties, namely, the DA bidding strategies of other participants, the RT electricity prices, and the demands of the strategic retailer, are represented explicitly via scenarios. Additionally, as shown in Fig. 1, there are many other uncertainties in the electricity markets, such as the RT bidding strategies of other participants, weather conditions, and power outage events in the power grid. Even though these additional uncertainties are not represented explicitly in the model, they are represented implicitly by the three types of uncertain parameters that are considered explicitly in the model. For instance, RT prices are affected by RT bidding strategies of other participants, renewable power productions, and power outage events, and RT demands are significantly affected weather conditions. In this circumstance, when the uncertain RT prices and demands are represented via scenarios in the proposed model, many other uncertainties are also taken into account implicitly.

In this paper, scenarios of uncertain parameters are generated by using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model-based method, which is widely used for stochastic decision-making problems in electricity markets [1]. To model the uncertain parameters accurately, a large number of scenarios are usually generated. This, however, may lead to a large-scale stochastic optimization model that cannot be solved within the required time frame. To reduce the computational burden, the fast forward scenario reduction method [31] is used to reduce the scenario number while preserving the statistical properties of the scenario sets as intact as possible.

3. Model formulation and conversion

In this section, the detailed formulation of the proposed model are provided in Sections 3.1 and 3.2, which is a bilevel nonlinear stochastic optimization problem that cannot be solved directly by using any existing solver. To address this issue, the proposed bilevel nonlinear optimization model is converted to a single-level nonlinear mathematical programming with equilibrium constraints (MPEC) problem in Section 3.3. Then, the nonlinear terms of the MPEC problem are linearized in Section 3.4 so that the problem is further converted to a single-level mixed integer linear programming (MILP) problem, which can be solved efficiently using the commercial solvers.

3.1. Upper level problem

The upper level problem (1) maximizes the expected total profit of the demand and virtual bidding in the two-settlement electricity market and is expressed as follows:

$$\max_{\Xi}(1-\beta)\sum_{tw}\pi_w\Bigg[-\sum_{ib}\lambda^{DA}_{(n:i\in\psi^I_n)tw}D^{SD}_{bitw} - \sum_{i}\lambda^{RT}_{(n:i\in\psi^I_n)tw}\left(D^{SR}_{itw}-\sum_{b}D^{SD}_{bitw}\right) + \sum_{v}\left(\lambda^{DA}_{(n:v\in\psi^V_n)tw}-\lambda^{RT}_{(n:v\in\psi^V_n)tw}\right)\left(P^{VI}_{vtw}-P^{VD}_{vtw}\right)\Bigg]+\beta\left(\zeta-\frac{1}{1-\alpha}\sum_{w}\pi_w\eta_w\right) \tag{1a}$$

Subject to:

$$0\le\lambda^{SD}_{bit}\le\lambda^{CapD}\qquad\forall\, b,\, i,\, t \tag{1b}$$

$$0\le\lambda^{VI}_{vt}\le\lambda^{CapD}\qquad\forall\, v,\, t \tag{1c}$$

$$0\le\lambda^{VD}_{vt}\le\lambda^{CapD}\qquad\forall\, v,\, t \tag{1d}$$

$$\sum_{b=1}^{B}D^{SDmax}_{bit}\le D^{SF}_{it}\qquad\forall\, i,\, t \tag{1e}$$

$$\sum_{v=1}^{V}\left(P^{VImax}_{vt}+P^{VDmax}_{vt}\right)\le P^{Vmax}_{t}\qquad\forall\, v,\, t \tag{1f}$$

$$0\le P^{VImax}_{vt}\le M_{vt}z_{vt}\qquad\forall\, v,\, t \tag{1g}$$

$$0\le P^{VDmax}_{vt}\le M_{vt}(1-z_{vt})\qquad\forall\, v,\, t \tag{1h}$$

$$z_{vt}\in\{0,1\}\qquad\forall\, v,\, t \tag{1i}$$

$$\eta_w\ge 0\qquad\forall\, w \tag{1j}$$

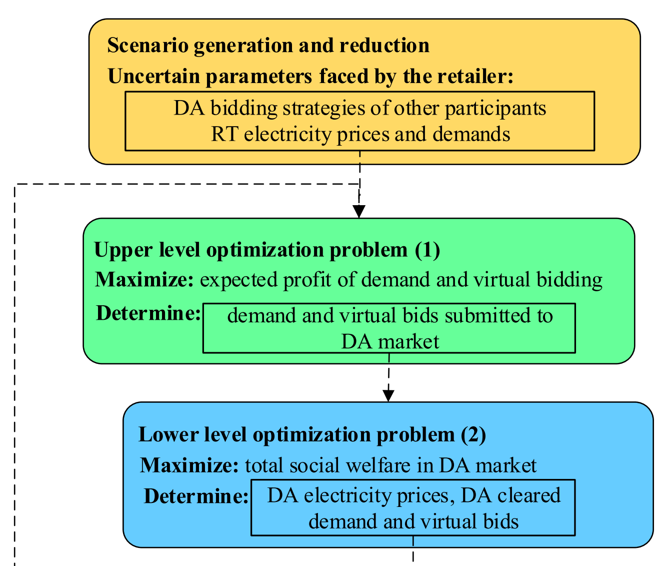


Fig. 2. Structure of the proposed bilevel stochastic optimization model.

$$\zeta - \eta_w \le - \sum_{bit} \lambda^{DA}_{(n:i\in\psi^I_n)tw} D^{SD}_{bitw} - \sum_{it} \lambda^{RT}_{(n:i\in\psi^I_n)tw} (D^{SR}_{itw} - \sum_b D^{SD}_{bitw}) + \sum_{vt} \left(\lambda^{DA}_{(n:v\in\psi^V_n)tw} - \lambda^{RT}_{(n:v\in\psi^V_n)tw} \right) (P^{VI}_{vtw} - P^{VD}_{vtw}) \quad \forall w \tag{1k}$$

where $\Xi = \{\lambda^{SD}_{bit}, \ \lambda^{VI}_{vt}, \ \lambda^{VD}_{vt}, \ P^{VImax}_{vt}, P^{VDmax}_{vt}, \ \zeta, \ \eta_w, \ \Xi^D\}$ is the set of the decision variables of the bilevel optimization problem, and Ξ^D is the decision variables existing in the lower level problem provided in Section 3.2.

The objective function (1a) maximizes two terms: 1) the sum of the negative energy purchasing costs and virtual bidding profits in the DA and RT electricity markets multiplied by 1-β; 2) the CVaR multiplied by β. Specifically, the term $\zeta - \frac{1}{1-\alpha}\sum_w \pi_w \eta_w$ is the CVaR with a confidence level α_s ($0 < \alpha_s < 1$), and can be denoted as $CVaR_{\alpha_s}$. The value of $CVaR_{\alpha_s}$ is equal to the expected profit of the $(1-\alpha_s) \times 100\%$ least profitable scenarios of the stochastic demand and virtual bidding strategy. In the proposed model, the CVaR is calculated by using the ancillary constraints (1j) and (1k), where η_w and ζ are ancillary variables. The detailed derivations for these formulations on the calculation of the CVaR can be found in [32]. The weight β represents the risk aversion parameter of the retailer, and a higher value of β indicates that the strategic retailer is more risk averse. In (1a), $\lambda^{DA}_{(n:i\in\psi^I_n)tw}$, $\lambda^{DA}_{(n:v\in\psi^V_n)tw}$, D^{SD}_{bitw}, P^{VI}_{vtw} and P^{VD}_{vtw} are the variables determined in the lower level problem (2).

As shown in (1a), the strategic retailer's incremental or decremental virtual bids tend to be submitted at the buses with positive and negative price differences between DA and RT markets, respectively. In contrast, the demand bids of the strategic retailer are decremental and tend to be submitted at the buses with negative price differences between DA and RT markets, because the power purchasing cost in the DA market is decreased with the DA price.

Constraints (1b)-(1d) enforce the acceptable DA bidding prices of the strategic retailer's demands and virtual units. Constraints (1e) and (1f) limit the bidding quantities based on the forecasted demands and the maximum capacity of the virtual units, respectively. Constraints (1g)–(1i) indicate that either an incremental or a decremental virtual bid can be submitted at each bus. Constraints (1j) and (1k) are used to compute the CVaR, which is the retailer's expected profit of the $(1-a) \times 100\%$ worst scenarios [32]. Constraint (1l) indicates that problem (1) is subject to the lower level problem (2) in Section 3.2.

3.2. Lower level problem

The lower level problem (2) models the DA market clearing process for each scenario w and is formulated as follows:

$$\min_{\Xi^D} \sum_v \lambda^{VI}_{vt} P^{VI}_{vtw} + \sum_{qj} \lambda^{CD}_{qjtw} P^{CD}_{qjtw} - \sum_{bi} \lambda^{SD}_{bit} P^{SD}_{bitw} - \sum_v \lambda^{VD}_{vt} P^{VD}_{vtw} - \sum_{el} \lambda^{OD}_{elt} D^{OD}_{eltw} \tag{2a}$$

Subject to:

$$\sum_{j\in\psi^J_n, q} P^{CD}_{qjtw} + \sum_{v\in\psi^V_n} P^{VI}_{vtw} - \sum_{i\in\psi^I_m, b} D^{SD}_{bitw} - \sum_{v\in\psi^V_n} P^{VD}_{vtw} - \sum_{l\in\psi^L_n, e} D^{OD}_{eltw} - \sum_{k|s(k)=n} f^D_{ktw} + \sum_{k|r(k)=n} f^D_{ktw} = 0: \lambda^{DA}_{ntw} \quad \forall n, \ t, w \tag{2b}$$

$$f^D_{ktw} = B_k(\delta^{DA}_{s(k)tw} - \delta^{DA}_{r(k)tw}): \varnothing_{ktw} \quad \forall k, t, w \tag{2c}$$

$$-C^{max}_k \le f^D_{ktw} \le C^{max}_k: \varnothing^{min}_{ktw}, \varnothing^{max}_{ktw} \quad \forall k, t, w \tag{2d}$$

$$0 \le D^{SD}_{bitw} \le D^{SDmax}_{bit}: \mu^{SDmax}_{bitw}, \mu^{SDmin}_{bitw}, \quad \forall b, i, t, w \tag{2e}$$

$$0 \le P^{VI}_{vtw} \le P^{VImax}_{vt}: \mu^{VImax}_{vtw}, \mu^{VImin}_{vtw} \quad \forall v, t, w \tag{2f}$$

$$0 \le P^{VD}_{vtw} \le P^{VDmax}_{vt}: \mu^{VDmax}_{vtw}, \mu^{VDmin}_{vtw} \quad \forall v, t, w \tag{2g}$$

$$0 \le P^{CD}_{qjtw} \le P^{CDmax}_{qjt}: \mu^{CDmax}_{qjtw}, \mu^{CDmin}_{qjtw} \quad \forall q, j, t, w \tag{2h}$$

$$0 \le D^{OD}_{eltw} \le D^{ODmax}_{elt}: \mu^{ODmax}_{eltw}, \mu^{ODmin}_{eltw} \quad \forall e, l, t, w \tag{2i}$$

$$-\pi \le \delta^{DA}_{ntw} \le \pi: \ \theta^{Dmax}_{ntw}, \theta^{Dmin}_{ntw} \quad \forall n/ref, t, w \tag{2j}$$

$$\delta^{DA}_{ntw} = 0: \theta^{D1}_{ntw} \quad n: ref, t, w \tag{2k}$$

where $\Xi^D = \{D^{SD}_{bitw}, P^{VI}_{vtw}, P^{VD}_{vtw}, P^{CD}_{qjtw}, D^{OD}_{eltw}, \lambda^{DA}_{ntw}, \varnothing_{ktw}, \varnothing^{min}_{ktw}, \varnothing^{max}_{ktw}, \mu^{SDmax}_{bitw}, \mu^{SDmin}_{bitw}, \mu^{Vmax}_{vtw}, \mu^{Vmin}_{vtw}, \mu^{CDmax}_{qjtw}, \mu^{CDmin}_{qjtw}, \mu^{ODmax}_{eltw}, \mu^{ODmin}_{eltw}, \theta^{Dmax}_{ntw}, \theta^{Dmin}_{ntw}, \theta^{D1}_{ntw}\}$ is the set of all decision variables of the problem (2), which includes both primal and dual variables. The dual variables are given following the colon in each constraint.

The objective function (2a) minimizes the total cost of the power offered by the virtual and generating units minus the revenue of the virtual units and demands in each scenario. The DA power balance considering the incremental and decremental virtual bids at each bus is provided in constraint (2b), and the power flow equation of each transmission line is given in constraint (2c). Constraint (2d) imposes the capacity limits of each transmission line. Constraint (2e)–(2i) limit the cleared bidding capacities of the virtual and generating units and demands. The voltage angle of each bus is limited in constraint (2j), and the reference bus of the system is defined in Constraint (2k).

3.3. An equivalent single-level mathematical programming with equilibrium constraints problem

The proposed bilevel optimization problem (1) and (2) can be converted into an equivalent single-level mathematical programming with equilibrium constraints (MPEC) problem through the KKT conditions of the lower level problem (2), which are provided as follows:

$$-\lambda^{SD}_{bit} + \lambda^{DA}_{ntw} + \mu^{SDmax}_{bitw} - \mu^{SDmin}_{bitw} = 0 \quad \forall b, \ i \in \psi^I_n, t, w \tag{3a}$$

$$\lambda^{VI}_{vt} - \lambda^{DA}_{ntw} + \mu^{VImax}_{vtw} - \mu^{VImin}_{vtw} = 0 \quad \forall \ v \in \psi^V_n, \ t, w \tag{3b}$$

$$-\lambda^{VD}_{vt} + \lambda^{DA}_{ntw} + \mu^{VDmax}_{vtw} - \mu^{VDmin}_{vtw} = 0 \quad \forall \ v \in \psi^V_n, \ t, w \tag{3c}$$

$$\lambda^{CD}_{qjtw} - \lambda^{DA}_{ntw} + \mu^{CDmax}_{qjtw} - \mu^{CDmin}_{qjtw} = 0 \quad \forall q, \ j \in \psi^J_n, t, w \tag{3d}$$

$$\sum_{k|s(k)} B_k \varnothing_{ktw} - \sum_{k|r(k)} B_k \varnothing_{ktw} + \theta^{Dmax}_{ntw} - \theta^{Dmin}_{ntw} = 0 \quad \forall n/ref, \ t, w \tag{3e}$$

$$\sum_{k|s(k)} B_k \varnothing_{ktw} - \sum_{k|r(k)} B_k \varnothing_{ktw} - \theta^{D1}_{ntw} = 0 \quad n: ref, \ t, w \tag{3f}$$

$$0 \le (D^{SDmax}_{bit} - P^{SD}_{bitw}) \perp \mu^{SDmax}_{bitw} \ge 0 \quad \forall b, i, \ t, w \tag{3g}$$

$$-\lambda^{OD}_{eltw} + \lambda^{DA}_{ntw} + \mu^{ODmax}_{eltw} - \mu^{ODmin}_{eltw} = 0 \quad \forall l \in \psi^L_n, e, t, w \tag{3h}$$

$$\lambda^{DA}_{s(k)tw} - \lambda^{DA}_{r(k)tw} - \varnothing_{ktw} + \varnothing^{max}_{ktw} - \varnothing^{min}_{ktw} = 0 \quad \forall k, t, w \tag{3i}$$

$$0 \le P_{bitw}^{SD} \perp \mu_{bitw}^{SD\min} \ge 0 \qquad \forall\, b, i, t, w \tag{3j}$$

$$0 \le (P_{vt}^{VI\max} - P_{vtw}^{VI}) \perp \mu_{vtw}^{VI\max} \ge 0 \qquad \forall\, v, t, w \tag{3k}$$

$$0 \le P_{vtw}^{VI} \perp \mu_{vtw}^{VI\min} \ge 0 \qquad \forall\, v, t, w \tag{3l}$$

$$0 \le (P_{vt}^{VD\max} - P_{vtw}^{VD}) \perp \mu_{vtw}^{VD\max} \ge 0 \qquad \forall\, v, t, w \tag{3m}$$

$$0 \le P_{vtw}^{VD} \perp \mu_{vtw}^{VD\min} \ge 0 \qquad \forall\, v, t, w \tag{3n}$$

$$0 \le (P_{qjt}^{CD\max} - P_{qjtw}^{CD}) \perp \mu_{qjtw}^{CD\max} \ge 0 \qquad \forall\, q, j, t, w \tag{3o}$$

$$0 \le P_{qjtw}^{CD} \perp \mu_{qjtw}^{CD\min} \ge 0, \qquad \forall\, q, j, t, w \tag{3p}$$

$$0 \le (D_{elt}^{OD\max} - D_{eltw}^{OD}) \perp \mu_{eltw}^{OD\max} \ge 0 \qquad \forall\, e, l, t, w \tag{3q}$$

$$0 \le D_{eltw}^{OD} \perp D_{eltw}^{OD\min} \ge 0, \qquad \forall\, e, l, t, w \tag{3r}$$

$$0 \le (C_k^{\max} - f_{ktw}^{D}) \perp \varnothing_{ktw}^{\max} \ge 0 \qquad \forall\, k, t, w \tag{3s}$$

$$0 \le (C_k^{\max} + f_{ktw}^{D}) \perp \varnothing_{ktw}^{\min} \ge 0 \qquad \forall\, k, t, w \tag{3t}$$

$$0 \le (\pi - \delta_{ntw}^{DA}) \perp \theta_{ntw}^{D\max} \ge 0 \qquad \forall\, n, t, w \tag{3u}$$

$$0 \le (\delta_{ntw}^{DA} + \pi) \perp \theta_{ntw}^{D\min} \ge 0 \qquad \forall\, n, t, w \tag{3v}$$

where the constraints (3a)-(3f) are the stationary conditions of the lower level problem (2); the constraints (3g)–(3v) are the complementarity conditions of (2).

3.4. Reformulate the MPEC as an mixed integer linear programming problem

The objective function (1a) and the constraints (1b)–(1k) and (3) form a nonlinear single-level MPEC problem, which has two kinds of nonlinear terms that can be linearized as follows.

1) The term $-\sum_{bi}\lambda_{(n:i\in\psi_n^I)tw}^{DA} D_{bitw}^{SD} + \sum_v \lambda_{(n:v\in\psi_n^V)tw}^{DA} P_{vtw}^{VI} - \sum_v \lambda_{(n:v\in\psi_n^V)tw}^{DA} P_{vtw}^{VD}$ in (1a) is bilinear and can be linearized as follows according to (3a)–(3c), (3i)–(3n), and the strong duality theorem.

$$\begin{aligned}
&-\sum\nolimits_{bi}\lambda_{(n:i\in\psi_n^I)tw}^{DA} D_{bitw}^{SD} + \sum\nolimits_v \lambda_{(n:v\in\psi_n^V)tw}^{DA}(P_{vtw}^{VI} - P_{vtw}^{VD})\\
&= \sum\nolimits_{bi}(\mu_{bitw}^{SD\min} - \mu_{bitw}^{SD\max} - \lambda_{bit}^{SD})D_{bitw}^{SD}\\
&\quad + \sum\nolimits_v(\mu_{vtw}^{VI\max} - \mu_{vtw}^{VI\min} + \lambda_{vt}^{VI})P_{vtw}^{VI}\\
&+ \sum\nolimits_v(\mu_{vtw}^{VD\min} - \mu_{vtw}^{VD\max} + \lambda_{vt}^{VD})P_{vtw}^{VD}\\
&= \sum\nolimits_{el}\lambda_{elt}^{OD} D_{eltw}^{OD} - \sum\nolimits_{qj}\lambda_{qjtw}^{CD} P_{qjtw}^{CD} - \sum\nolimits_{qj}\mu_{qjtw}^{CD\max} P_{qjt}^{CD\max}\\
&\quad - \sum\nolimits_{el}\mu_{eltw}^{OD\max} D_{elt}^{OD\max}\\
&- \sum\nolimits_k C_k^{\max}(\varnothing_{ktw}^{D\max} + \varnothing_{ktw}^{D\min}) - \sum\nolimits_n \pi(\theta_{ntw}^{D\max} + \theta_{ntw}^{D\min})
\end{aligned} \tag{4}$$

2) The MPEC model includes nonlinear complementarity constraints (3g)–(3v). According to [33], a complementarity constraint in the form of $0 \le P \perp Q \ge 0$ can be replaced by the following formulation:

$$P \ge 0,\ Q \ge 0;\ P \le \mu M;\ 0 \le Q \le (1-\mu)M;\ \mu \in \{0, 1\}$$

where M is a sufficiently large constant.

Therefore, the MPEC problem is transferred into a single-level MILP problem, which can be solved efficiently by using existing commercial solvers.

4. Case studies and results

4.1. Simulation setup

To verify the effectiveness of the proposed model, the six-bus test system provided in [34] is used to perform illustrative case studies in Section 4.2–4.5, and the IEEE 118-bus system is used in Section 4.6 to further verify the proposed model's applicability for a large system [11]. The historical demand data of the retailer and RT electricity prices are obtained from the PJM electricity market website [35]. It is assumed that virtual bidding can be used at all buses of the systems and all of the virtual units are owned by the strategic retailer. Five hundred scenarios are first generated for each uncertain parameter based on the SARIMA model and then are reduced to eight. The uncertainties of other participants' DA bidding prices are only modelled and studied in 4.5, but are not considered in the other sections for simplicity. The proposed MILP model is solved by using Yalmip [36] and Gurobi 7.0 in MATLAB [37]. The computer used for simulation studies has a 3.50-Ghz, 4- core CPU and a 32-GB RAM.

4.2. Results of risk-neutral joint demand and virtual bidding strategy

The six-bus test system used in this section is shown in Fig. 3 [34]. The system has 8 generating units and 4 aggregated demands. D1 at Bus 3 is assumed to be the demand of the strategic retailer. D2-D4 are the demands of other retailers or consumers, and their bid data are obtained from [34]. P1-P8 are conventional generating units whose offer data are provided in Table 1.

By setting the risk aversion degree β to be zero, the bilevel nonlinear optimization problem (1) and (2) is converted into a single-level MILP problem, which is solved to obtain the strategic retailer's risk-neutral joint demand and virtual bidding strategy for a typical day. In this study, the maximum virtual capacity is set to be 60 MW. The price differences between the DA and RT markets at the six buses over 24 h of the day are shown in Fig. 4. The incremental and decremental virtual bidding capacities at the six buses are provided in Fig. 5. The results show that the location and type of virtual bids depend on the properties of price differences between DA and RT markets. Most of the incremental virtual bids are used at Bus 4 because it has the largest positive price differences during all of the 24 h. In contrast, most of the decremental virtual bids are used at Bus 2 because it has the largest negative price differences in some hours.

Fig. 6 shows the RT demands of the strategic retailer and the DA and RT electricity prices at Bus 3 where the strategic retailer's demands are located. Fig. 7 shows the expected profits of the strategic retailer over 24 h, where the profit of demand bidding is negative because the demand bidding is purchasing power in the electricity market. Therefore, the absolute value of the negative profit is equal to the cost of purchasing power for the strategic retailer's RT demands, which increases

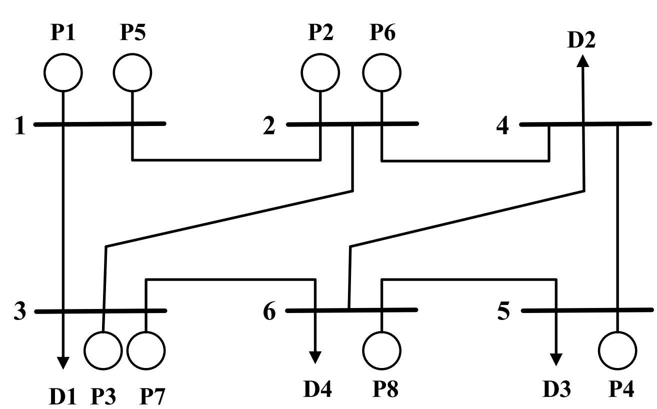


Fig. 3. The six bus test system.

Table 1
Data for the conventional generating units.

Unit #	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
P_{1j}^{CDmax} (MW)	25	15.8	15	140	2.4	68.9	76	54.3
P_{2j}^{CDmax} (MW)	25	0.2	15	97.5	3.4	49.3	15.2	38.8
P_{3j}^{CDmax} (MW)	20	3.8	10	52.5	3.6	39.4	22.8	31
P_{4j}^{CDmax} (MW)	20	0.2	10	70	2.4	39.4	15.2	31
λ_{1j}^{CD} ($/MWh)	31.6	18.9	0	32.6	39.8	17.1	19.5	16.9
λ_{2j}^{CD} ($/MWh)	34.1	19.4	0	34.5	40.4	18.1	20.3	17.4
λ_{3j}^{CD} ($/MWh)	36.8	27.3	0	36.1	45.6	18.9	23.6	18.2
λ_{4j}^{CD} ($/MWh)	38.6	27.6	0	37.6	51.7	19.9	27.1	19.1

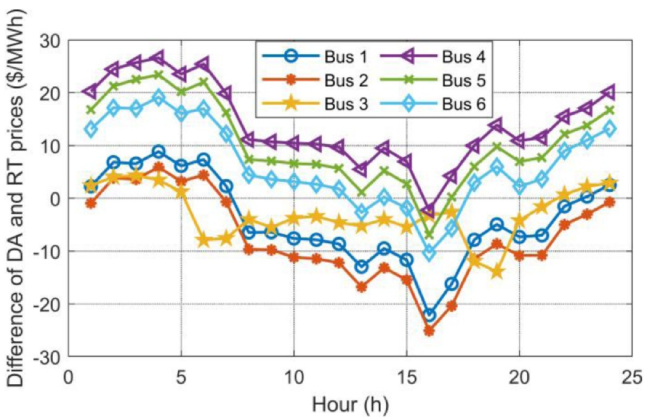


Fig. 4. Differences of DA and RT electricity prices at the six buses over 24 h of one day.

with the RT demand and the electricity price at Bus 3. As shown in Figs. 4 and 7, the profit of virtual bidding depends on the price differences when the maximum virtual capacity is fixed. The highest profit of virtual bidding occurs in the 4th hour in which the price difference has the largest absolute value at Bus 4. The profits of virtual bidding from the 8th to the 12th hour are much lower than that in the 4th hour, because the absolute price differences in those hours are much smaller than that in the 4th hour.

4.3. Impacts of maximum virtual capacities and load levels

In this study, different maximum virtual bidding capacities and load levels are used in the risk-neutral bidding problem to analyze their impacts on the profitability of the strategic retailer. The maximum virtual bidding capacity is changed from 0 to 280 MW with an increment of 40 MW. The strategic retailer's RT demands is multiplied by a load level coefficient, which is changed from 0.2 to 3.2 with an increment of 0.4. As shown in Fig. 6, the original peak demand of the strategic retailer is 84.8 MW, which occurs in the 16th hour of the day. Therefore, when the load level coefficient is increased from 0.2 to 3.2, the peak demand of the strategic retailer is increased from 17 MW to 255 MW.

Fig. 8 shows that the expected total profit of the strategic retailer increases with the maximum virtual bidding capacity but decreases with the load level coefficient. When the maximum virtual bidding capacity is very large or the load level is very small, the profit of virtual bidding can cover the cost of buying power for the strategic retailer's RT demands, thus making the total profit positive. Additionally, the rate of

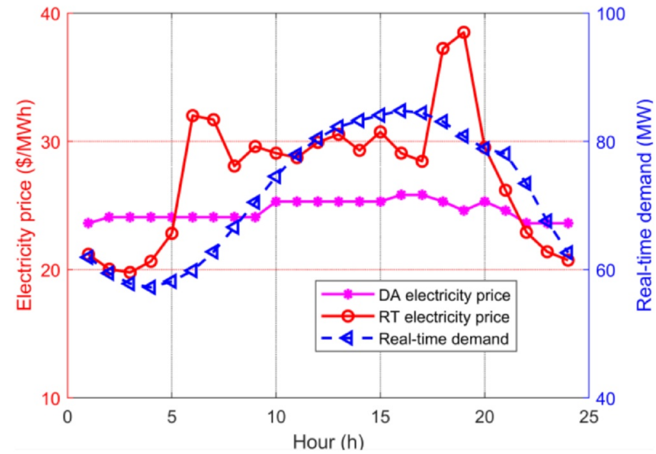


Fig. 6. RT demands of the strategic retailer and DA and RT electricity prices at Bus 3 of a day.

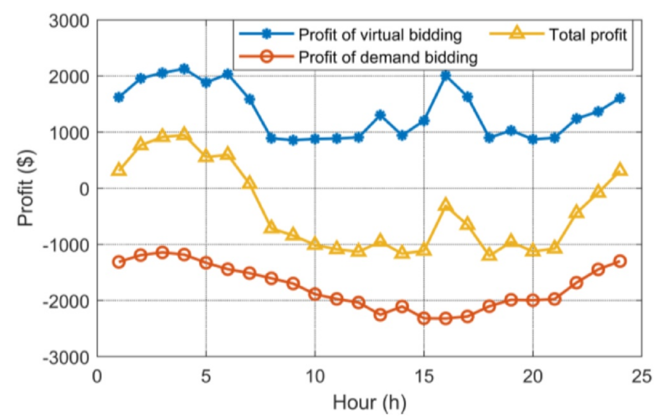
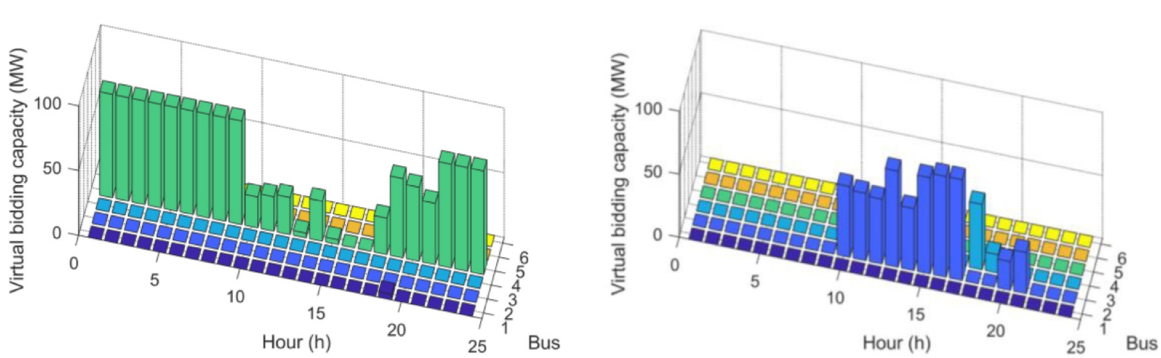


Fig. 7. Expected profits of the strategic retailer over 24 h of a day.



(a) **(b)**

Fig. 5. **(a)** Incremental and **(b)** decremental virtual bidding capacities at the six buses in 24 h of one day.

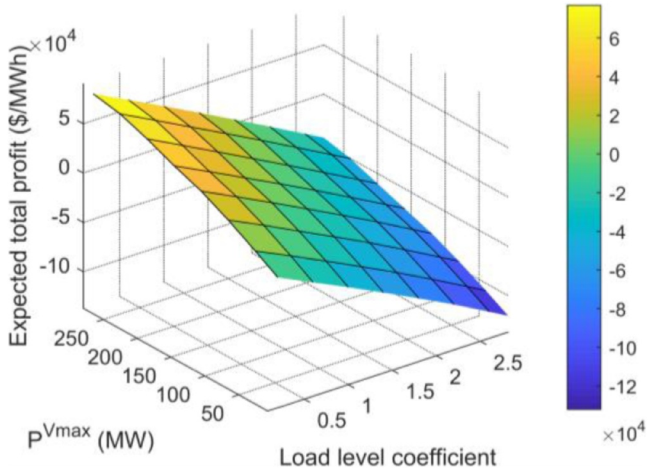


Fig. 8. The expected total profit of the strategic retailer vs. the maximum virtual bidding capacity and load level coefficient.

increase of the total profit with respect to the virtual bidding capacity is different when the virtual capacity is in different ranges. For instance, when the peak demand is 255 MW and the virtual bidding capacity is increased from 40 to 80 MW, the total profit is increased by $14,544. However, when the virtual bidding capacity is increased from 240 MW to 280 MW, the total profit is only increased by $6240. This is because that the price differences between the DA and RT markets are smaller when the maximum virtual bidding capacity is between 240 MW and 280 MW. In this circumstance, it may not be beneficial for the strategic retailer to further increase its virtual bidding capacity due to the need for increasing the credit.

4.4. Impact of risk management

In this study, the risk aversion parameter β in the proposed optimization model is changed from 0 to 0.9 with an increment of 0.1 to study its impact on the expected profit and CVaR of the strategic retailer; and the number of scenarios of the uncertain parameters is still the same as that in Section 4.2. The maximum virtual bidding capacity is set to be 0, 60, 120, and 180 MW. The simulation results of the expected total profit and CVaR versus risk aversion degree β at different maximum virtual bidding capacities are shown in Figs. 9 and 10, respectively.

When β increases, the expected total profit and CVaR decreases and increases, respectively. This means that a larger risk aversion degree leads to a less expected total profit but a smaller risk. When β is changed from 0 to 0.1, the expected total profit only decreases slightly by about 0.87%, 1.56%, 0.19%, and 0.76% at the four different maximum virtual bidding capacities, respectively, but the CVaR increases significantly by about 69.19%, 56.05%, 71.74%, and 82.29%, respectively. The results show that compared with the risk-neutral bidding strategy, a small risk aversion parameter can significantly improve the expected profit of the worst scenarios while only decreasing the expected total profit slightly. However, when β is larger than 0.1, further increasing its value can only improve the CVaR slightly. These results indicate that choosing β to be 0.1 would be the best tradeoff of the joint demand and virtual bidding for the strategic retailer.

The simulation results in Figs. 9 and 10 also show that, although virtual bidding can improve both the expected profit and the CVaR, the improvement tends to decrease with the increase of the maximum virtual bidding capacity due to the reductions of the DA and RT price difference and the increased virtual bids cleared in the DA market. For instance, when the risk aversion degree is 0.1 and the maximum virtual capacity is increased from 0 to 60 MW, the expected profit and CVaR are increased by $28,919 and $22,632, respectively, the largest absolute DA and RT price difference of the 6 buses is decreased from 22.06$/MWh to 20.31$/MWh, and the total cleared virtual bid is increased from 0 MWh to 1431 MWh. However, when the maximum virtual capacity is increased from 120 MW to 180 MW, the expected profit and CVaR are only increased by $18,096 and $8787, respectively, the largest absolute price difference of the 6 buses is decreased from 19.85$/MWh to 18.64$/MWh, and the total cleared virtual bid is only increased by 1084 MWh from 2757 MWh to 3841 MWh.

4.5. Impact of other participants' uncertain bidding strategies

In this section, the impact of the uncertainties of other participants' bidding strategies in the proposed model is studied. When the DA bidding prices of P1-P8 cannot be forecasted accurately, they need to be represented using scenario sets instead of deterministic values. Specifically, the DA bidding price of the power producer j in the time period t is assumed to follow a normal distribution $\mathrm{N}(\lambda_{tj}^{CD}, \sigma_{tj}^2)$, where λ_{tj}^{CD} is the deterministic value provided in Table 1 and the standard variance σ_{jt} is used to characterize the volatility of the forecast errors of other participants' bidding prices.

Fig. 11 shows the results of the total expected profit and CVaR of the strategic retailer when the standard variance of other participants' bidding price forecast errors is increased from 0^2/MWh^{2}to 5^2/MWh^2. A larger standard variance indicates that it is more difficult for the retailer to forecast other participants' bidding prices and their scenarios generated by the normal distribution are more volatile. When the value of standard variance is increased from 0^2/MWh^2 to 5^2/MWh^2, the total expected profit and CVaR decrease by about $1192 and $5235, respectively. Therefore, the increased uncertainties of other market participants lead to a decrease of the expected profit and an increase of the risk of the strategic retailer. Additionally, the CVaR is more sensitive to the bidding price forecast errors than the total expected profit, which indicates that the expected profits of the worst scenarios are affected more significantly by the uncertainties of other market participants' bidding strategies.

4.6. Results of IEEE 118-bus system

In this section, the IEEE 118-bus system is used to further verify the applicability of the proposed model for a larger system [11]. The data of the power producers' DA generation offers and transmission capacities are provided in [11]. The maximum virtual capacity is set to be 400 MW. The demand data of D1-D4 in Section 4.2 are multiplied by 3 and used in this system. D1 is assumed to be located at Bus 1; while D2, D3, and D4 are distributed evenly at Buses 15–19, Buses 41–45, and Buses 71–75, respectively.

The risk-neutral demand and virtual bidding strategies of the

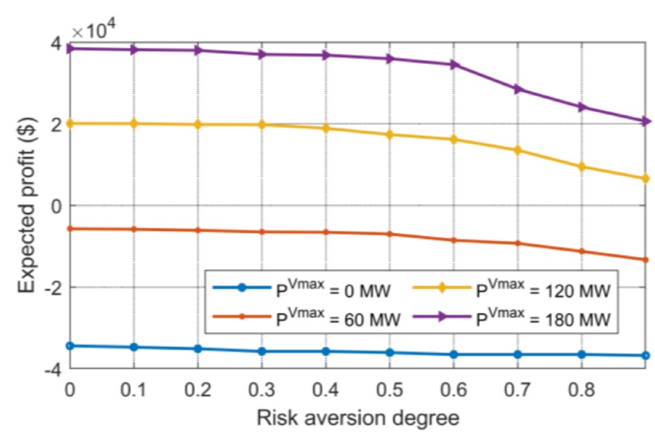


Fig. 9. Impacts of the risk aversion degree on the expected total profit at different maximum virtual capacities.

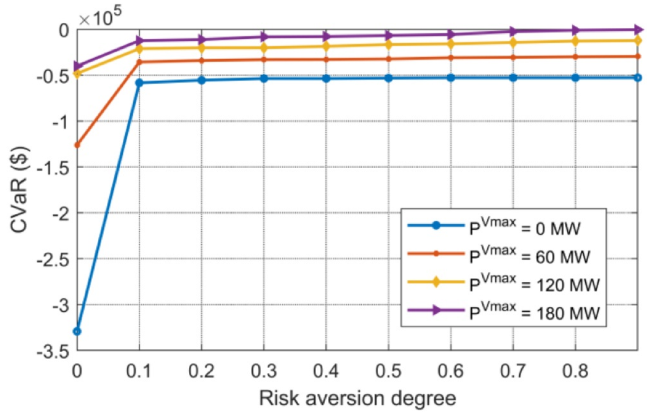


Fig 10. Impacts of the risk aversion degree on the CVaR at different maximum virtual capacities.

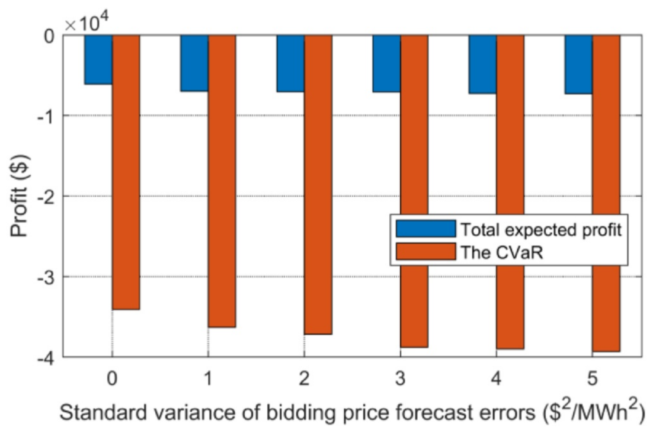


Fig. 11. Impact of other participants' bidding price forecast errors on the total expected profit and CVaR of the strategic retailer.

strategic retailer are firstly generated. The computation time of solving the optimization problem is about 467.4 s. The price differences between DA and RT markets for different time periods and buses are shown in Fig. 12. The generated DA bidding quantiles, prices, and locations of the strategic retailer using virtual bidding are given in Table 2.

As shown in Fig. 12 and Table 2, the generated demand and virtual bids are related to the spatial temporal price differences between DA and RT markets, which has been discussed in Section 4.1. For instance, incremental virtual bids are submitted at Bus 35 in 20 out of 24 h of the day, because in those hours the expected hourly price differences between DA and RT markets at Bus 35 are in the range of $23.6 - 30.3$ \$/MWh, which are positive. In the 16th hour of the day, decremental virtual bids are submitted at Bus 3 and Bus 23, where the expected hourly price differences between DA and RT markets are negative values of -24.5 \$/MWh and -24.2 \$/MWh, respectively. Since virtual bidding can be used at all of the buses but the total quantity of virtual bids is limited by the credit in the strategic retailer's trading account, the virtual bids are only submitted at 6 buses of the IEEE 118-bus power system with largest DA and RT price differences, meaning that the quantities of the virtual bids at most of the 118 buses are zero. In contrast, the demand bidding of the strategic retailer can only be used at Bus 1. As long as the DA price is lower than the RT price at Bus 1, the strategic retailer would prefer to submit DA demand bids at Bus 1 to purchase power at a lower price in the DA electricity market.

Additionally, the total expected profit and CVaR of the strategic retailer are obtained when the risk-aversion parameter is increased from 0 to 1 with an increment of 0.1, and the results are provided in Fig. 13. It is shown that the strategic retailer's total expected profit and CVaR are decreased and increased with the increase of the risk-aversion parameter, respectively, which indicates that the retailer using virtual bidding can effectively manage the potential risks in the markets based on its risk preference.

5. Conclusion

This paper proposed a bilevel stochastic optimization model for generating the optimal joint demand and virtual bidding strategy for a strategic retailer in short-term electricity markets. In the proposed model, virtual bidding is used to improve the strategic retailer's market power in the DA market by trading at multiple buses; and the uncertain RT demands of the strategic retailer and RT electricity prices in the market are represented by using scenarios. The proposed bilevel model was converted into a single-level MILP problem using the duality theory, KKT condition and big M method. By solving the single-level MILP problem using an existing solver, the optimal DA demand and virtual bidding strategies were generated simultaneously.

Case studies were carried out for a strategic retailer with virtual bidding in a six-bus test system and the IEEE 118-bus system, respectively. The results showed that the virtual bidding could improve the profitability and decrease the risk of the strategic retailer due to its increased trading volume in the DA and RT markets. The impacts of different load levels, maximum virtual bidding capacities, risk aversion parameter, and bidding prices of other market participants on the strategic retailer's profit and risk were studied, and the results showed that these factors could affect the retailer's joint demand and virtual bidding strategy significantly.

In the future research, the potential collusions between multiple strategic players can be considered in the model for generating the bidding strategies. In this circumstance, the demand and virtual bids can be submitted by different market participants with cooperation, and their utility functions with different risk preferences should be taken into account simultaneously. Moreover, the profit allocation mechanism for multiple strategic market players also needs to be investigated in detail. Additionally, if the RT power trading volume of some electricity market is limited and the retailer has flexible resources in the RT market, it is also reasonable to consider the retailer using virtual bidding as a price-maker in the RT market, by which the impacts of the retailer's market power on the RT electricity prices can be modelled and studied in detail.

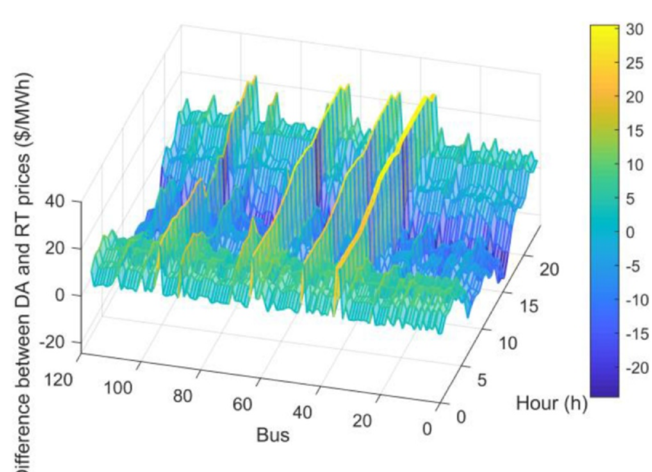


Fig. 12. Expected price differences between DA and RT markets of the IEEE 118-bus system.

Table 2
Results of the strategic retailer' DA demand and virtual bids in IEEE 118-bus system.

Hour	Demand bid		Incremental virtual bid			Decremental virtual bid		
	Quantity (MW)	Price ($/MWh)	Quantity (MW)	Price ($/MWh)	Bus No.	Quantity (MW)	Price ($/MWh)	Bus No.
1	182.9	38.5	296.9	0	35	103.0	38.5	88
2	150.3	38.1	195.0	0	35	67.5	38.1	15
						137.5	38.1	33
3	170.5	38	195.0	0	35	67.5	38.0	15
						137.5	38.0	33
4	150.3	38	195.0	0	35	67.5	38.0	15
						137.5	38.0	33
5	153.4	37.3	0	N/A	N/A	400.0	37.3	88
6	153.4	37.3	0	N/A	N/A	400.0	37.3	88
7	185.3	38.1	296.9	0	35	103.1	38.1	88
8	153.4	39.6	0	N/A	N/A	400.0	39.6	103
9	173.1	40.5	284.5	0	35	115.5	40.5	3
10	220.4	42.5	284.5	0	35	115.5	42.5	3
11	161.1	45	331.1	0	35	68.9	45.0	3
12	161.1	45	331.1	0	35	68.9	45.0	3
13	243.5	45	331.1	0	35	68.9	45.0	3
14	161.1	45	331.1	0	35	68.9	45.0	3
15	179.1	43.2	261.3	0	35	138.7	43.2	3
16	251	45	0	N/A	N/A	356.9	45.0	3
						43.1	45.0	23
17	195.2	45	195.3	0	35	204.7	45.0	3
18	161.1	45	331.1	0	35	68.9	45.0	3
19	161.1	45	331.1	0	35	68.9	45.0	3
20	161.1	45	331.1	0	35	68.9	45.0	3
21	161.1	45	331.1	0	35	68.9	45.0	3
22	143.3	45	322.2	0	35	77.8	45.0	15
23	144.3	40	400.0	0	35	0	N/A	N/A
24	147.3	39.6	340.3	0	35	59.7	39.6	88

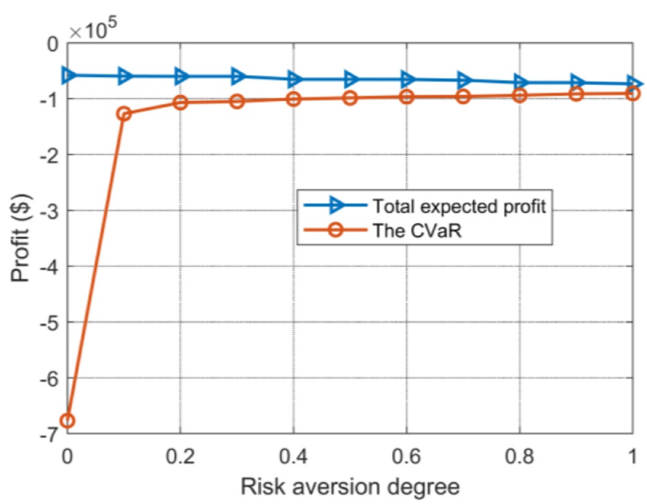


Fig. 13. Impact of the risk aversion degree on the total expected profit and CVaR of the strategic retailer.

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Dongliang Xiao: Conceptualization, Methodology, Software, Validation, Formal Analysis, and Writing-Original Draft Preparation.

Josue Campos do Prado: Methodology, Data Curation, and Writing-Original Draft Preparation.

Wei Qiao: Conceptualization, Reviewing and Editing, Supervision, Project Administration, and Funding Acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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