Optimal Price-maker Trading Strategy of Wind Power Producer Using Virtual Bidding

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***Abstract*—This paper proposes a stochastic optimization model for generating the optimal price-maker trading strategy for a wind power producer using virtual bidding, which is a kind of financial tool available in most electricity markets of the United States. In the proposed model, virtual bidding is used to improve the wind power producer's market power in the day-ahead (DA) market by trading at multiple buses, which are not limited to the locations of the wind units. The optimal joint wind power and virtual trading strategy is generated by solving a bi-level nonlinear stochastic optimization model. The upper-level problem maximizes the total expected profit of the wind power and virtual bidding while using the conditional value at risk (CVaR) for risk management. The lower-level problem represents the clearing process of the DA market. By using the Karush-Kuhn-Tucker (KKT) conditions, duality theory, and big-*M* method, the bi-level nonlinear stochastic model is firstly transferred into an equivalent single-level stochastic mathematical program with the equilibrium constraints (MPEC) model and then a mixed-integer linear programming (MILP) model, which can be solved by existing commercial solvers. To reduce the computational cost of solving the proposed stochastic optimization model for large systems, a method of reducing the number of buses considered for virtual bidding is proposed to simplify the stochastic MPEC model by reducing its decision variables and constraints related to virtual bidding. Case studies are performed to show the effectiveness of the proposed model and the method of reducing the number of buses considered for virtual bidding. The impacts of the transmission limits, wind unit location, risk aversion parameters, wind power volatility, and wind and virtual capacities on the price-maker trading strategy are also studied through case studies.**

***Index Terms*—Bi-level optimization, electricity market, risk management, stochastic optimization, virtual bidding, wind power.**

NOMENCLATURE

A. Indices and Sets

ϕ_n	Set of buses connected to bus n
ψ_n^I	Set of wind units located at bus n
ψ_n^J	Set of conventional units located at bus n
ψ_n^L	Set of demands located at bus n
ψ_n^V	Set of virtual units located at bus n
b	Index of energy blocks of a conventional unit, $b \in \{1, 2, \ldots, B\}$
e	Index of demand blocks, $e \in \{1, 2, \ldots, E\}$
i	Index of wind units owned by wind power producer, $i \in \{1, 2, \ldots, I\}$
j	Index of conventional units, $j \in \{1, 2, \ldots, J\}$
k	Index of transmission lines, $k \in \{1, 2, \ldots, K\}$
l	Index of demands, $l \in \{1, 2, \ldots, D\}$
n	Index of system buses, $n \in \{1, 2, \ldots, N\}$
p	Index of energy blocks of a wind unit, $p \in \{1, 2, \ldots, P\}$
$r(k)$	Receiving-end bus of transmission line k
$s(k)$	Sending-end bus of transmission line k
t	Index of time periods, $t \in \{1, 2, \ldots, T\}$
v	Index of virtual units owned by wind power producer, $v \in \{1, 2, \ldots, V\}$
w	Index of scenarios, $w \in \{1, 2, \ldots, \Omega\}$

B. Decision Variables

δ_{nt}^{DA}	Voltage angle of bus n in period t in day-ahead (DA) market
ζ	Auxiliary variable used to compute conditional value at risk (CVaR)
η_w	Auxiliary variable used to compute the CVaR
λ_{nt}^{DA}	DA locational marginal price (LMP) at bus n in period t
λ_{vt}^{VD}	Bid price of virtual unit v in period t in DA market when a decremental bid is used
λ_{vt}^{VI}	Bid price of virtual unit v in period t in DA market when an incremental bid is used
λ_{pit}^{WD}	Offer price of block p of wind unit i in period t in DA market
μ	An ancillary binary variable used for model linearization
$CVaR_\alpha$	CVaR with confidence level α

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f_{kt}^{D}	Power flow of transmission line k in period t in DA market
P_{bjt}^{CD}	Cleared power of block b of conventional unit j in period t in DA market
P_{elt}^{LD}	Cleared power of block e of demand l in period t in DA market
P_{vt}^{VD}	Cleared power of virtual unit v in period t in DA market when a decremental bid is used
$P_{vt}^{VD,\max}$	The maximum decremental bid capacity of virtual unit v in time period t in DA market
P_{vt}^{VI}	Cleared power of virtual unit v in period t in DA market when an incremental bid is used
$P_{vt}^{VI,\max}$	The maximum incremental bid capacity of virtual unit v in time period t in DA market
P_{pit}^{WD}	Cleared power of block p of wind unit i in period t in DA market
$P_{pit}^{WD,\max}$	The maximum power of block p of wind unit i in period t in DA market
z_{vt}	Binary variable for virtual unit v in period t, which is equal to 1 if an incremental bid is generated and 0 if a decremental bid is generated, respectively

C. Parameters

α	Per-unit confidence level
β	Risk aversion parameter of wind power producer
σ_{it}	Standard variance of wind power forecasting errors of wind unit i in period t in real-time (RT) market
λ	Wind volatility coefficient
λ^{CapD}	Cap bid price in DA market
λ_{bjt}^{CD}	Offer price of block b of conventional unit j in period t in DA market
λ_{elt}^{LD}	Bid price of block e of demand l in period t in DA market
λ_{ntw}^{RT}	RT LMP at bus n in period t in scenario w
π_{w}	Probability of occurrence of scenario w
B_{k}	Imaginary part of admittance of line k
$C_{k}^{\max}$	Transmission capacity of line k
M	A sufficiently large constant used for model linearization
P_{itw}^{WR}	RT power production of wind unit i in period t in scenario w
$P_{bjt}^{CD,\max}$	The maximum power of block b of conventional unit i in period t in DA market
$P_{elt}^{LD,\max}$	The maximum power of block e of demand l in period t in DA market
$P^{V,\max}$	The maximum total capacity of virtual units in DA market
P_{it}^{WF}	Deterministic wind power forecasting value of wind unit i in period t in RT market
$P_{i}^{W,\max}$	The maximum capacity of wind unit i

I. Introduction

MORE and more wind power producers have been selling wind power in competitive electricity markets to earn profits instead of through power purchasing agreements at fixed prices [1]. Under this circumstance, wind power producers not only need to handle the uncertainties of their generation but also face the volatility of the electricity prices in the markets. To account for uncertainties, stochastic optimization models have been widely used to generate trading strategies for wind power producers to participate in the electricity market [1]-[7]. According to the projection of U.S. Department of Energy, 35% of the electricity in the U.S. will be produced from wind energy by 2050 [8]. If the penetration levels of wind energy in some regions are high enough to influence the clearing outcomes of electricity markets, the wind power producers with large capacities need to be modeled as price-makers instead of price-takers in the electricity market [1]-[6], and their market power could be considered by using bi-level optimization models [1]-[5] or residual demand curves [6].

In the literature, demand response (DR) programs, energy storage, and financial derivatives have been used to improve the profits of wind power producers [5]-[7], [9]. In [5], the wind power producer could behave strategically in the day-ahead (DA) market and set DR contracts with a DR aggregator to alleviate the risk caused by its production uncertainty. In [6], [7] and [9], wind power production and energy storage were coordinated to mitigate the wind power imbalance in the electricity market; and the integrated wind power and energy storage system in the electricity market was modeled either as a price-maker [6] or a price-taker [7], [9]. Additionally, the purchasing option contract was also a financially competitive way to hedge against risks for a wind power producer [10]. However, no work has been reported in the literature to use a kind of pure financial tool called virtual bidding, which is available in the U.S. electricity markets, for wind power producers to hedge against risks caused by uncertainties.

Virtual bidding was first introduced to the PJM electricity market in June 2000 [11], and is currently available in most electricity markets in the U.S. The current competitive electricity markets in the U.S. usually have a two-settlement structure, which consists of a DA market and a real-time (RT) market, and virtual bidding is trading power in DA and RT markets without physically producing or consuming it. Virtual bidders can buy or sell power in the DA market and then zero it out in the RT market. The profit of a virtual bidder comes from the price differences between the DA and RT markets. In 2013, the cleared virtual bids in the five major electricity markets in the U.S. accounted for about 13% of the total load [12].

The advantages and disadvantages of virtual bidding were briefly discussed in [13]. In [14] and [15], virtual bidders were considered in the market clearing models; and it was concluded that the perfect virtual bidding could reduce the price differences between the DA and RT markets and increase the efficiency of the electricity market. By analyzing the historical data in the California wholesale electricity market, [16] and [17] found that the price differences between the DA and RT markets were reduced after the introduction of virtual bidding. The data analysis results of the New York wholesale electricity market also showed that virtual bidding could reduce the price volatility [18]. Several literature also addressed some drawbacks of the participation of virtual bidders [19]-[24]. Reference [19] showed that virtual bidders might earn profits without improving the efficiency of the electricity market in some situations due to the complexity of power grid operation. If the virtual bidders can not forecast the results of DA and RT markets accurately [20], or the power transmission lines are congested [21], the price differences between the DA and RT markets may not be reduced by virtual bidding. Moreover, [22] addressed that virtual bidding could be used to manipulate DA prices at some buses and increase the value of financial transmission right (FTR). In this case, the virtual bidding could be uneconomic and treated as a violation of the anti-manipulation rule by Federal Energy Regulatory Commission (FERC), and the virtual bidders need to pay heavy penalties for it [23]. Additionally, [24] analyzed the virtual bidding used by a cyber-data attacker, which brought financial losses to the power system. Reference [25] addressed that virtual bidding was an essential part of an efficient market design and should be estimated under a broad framework considering the uncertainties and risks, while most of the drawbacks in the literature were mainly concluded based on individual cases.

Most existing literature studied the virtual bidding used by financial participants [14]-[21], FTR holders [22], and cyber-data attackers [24] in electricity markets. However, the participants that own physical asserts in the power grid, such as wind power generation units, can also use virtual bidding to improve their profits and manage risks, and these participants are referred to as physical participants [26]. In practice, the proportion of virtual bidding used by physical participants is quite large in some wholesale electricity markets. In the PJM electricity market, about 63.5% and 55.2% of the cleared virtual bids came from physical participants in 2016 and 2017, respectively [26]. In this case, physical participants can co-optimize the profits brought by physical assets and virtual bidding simultaneously in the two-settlement electricity market. Moreover, if the physical participant is a price-maker, virtual bidding can help it influence the electricity market outcomes by trading at multiple buses, which are not limited to the locations of the physical assets. Therefore, it is necessary to model and analyze the virtual bidding strategies used by physical participants, which can also help market operators make better market rules or policies related to virtual bidding.

This paper proposes a stochastic optimization model for generating the optimal price-maker trading strategy for a wind power producer using virtual bidding in the electricity market. The main contributions of this paper are threefold.

1) The optimal wind power and virtual bidding strategies can be jointly generated by the proposed model based on the risk preference of the wind power producer. In this paper, the market power of the wind power producer in the DA market is improved by using virtual bidding at multiple buses, which are not limited to the locations of the wind units.

2) Different from the existing research on virtual bidding used by financial participants, this paper studied the virtual bidding used by a price-maker physical participant via detailed mathematical formulation. Such a study can help the market operators analyze the related market activities considering multiple factors, such as transmission line limits, physical unit location, risk aversion parameters, and wind power volatility, and then make better rules or policies in practice.

3) To reduce the computational cost of solving the proposed stochastic optimization model for large systems, a method of reducing the number of buses considered for virtual bidding is proposed to simplify the proposed model by reducing its decision variables and constraints related to virtual bidding.

The remainder of this paper is organized as follows. Section II presents the problem description. Section III presents the bi-level stochastic optimization model for generating the price-maker trading strategy for a wind power producer with virtual bidding and the solution method for the model. Section IV presents the validation results of the proposed strategy using case studies. Section V concludes this paper.

II. Problem Description

A. Market Framework

Figure 1 shows a typical time framework of a two-settlement electricity market in the U.S.. In the DA market, which is a forward market cleared by the independent system operator (ISO) one day before the operating day, the market participants can buy or sell power based on their expected generation or demands, respectively, at the DA electricity price. In contrast, the RT market is a physical market designed to balance the expected and actual electricity on the operating day, where the deviations need to be settled at the RT electricity price.

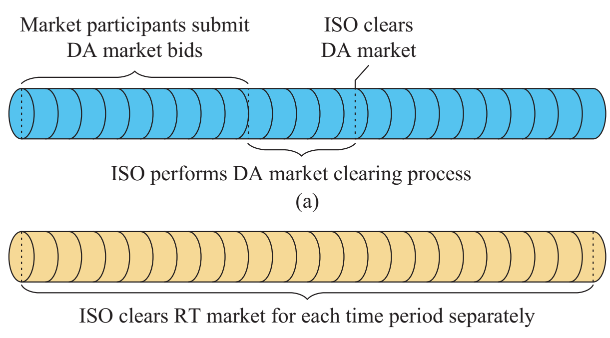

Fig. 1. Typical time framework of two-settlement electricity market. (a) DA market. (b) RT market.

For a wind power producer, the wind power committed in the DA market may be different from that produced on the operating day, and the deviation should be settled at the RT electricity prices. For a virtual trader without physical assets, the profit obtained from virtual bidding is related to the price differences between the DA and RT markets. If a virtual trader predicts that the DA electricity price will be higher than the RT electricity price, it will earn profits by submitting an incremental virtual bid to sell power at the DA electricity price and buy it back at the RT electricity price. On the contrary, if the virtual trader predicts that the DA electricity price will be lower than the RT electricity price, it will earn profits by submitting a decrement virtual bid to buy power at the DA electricity price and sell it at the RT electricity price. Therefore, if a wind power producer uses virtual bidding, the wind power and virtual bids will be submitted to the DA market simultaneously and settled at the DA electricity price; and then in the RT market, all the deviations caused by DA wind power and virtual bids will be settled at the RT electricity price.

In this paper, it is assumed that virtual bidding can be used at all of the buses in the power network and there is one virtual unit at each bus. The total bids of all virtual units cannot exceed the maximum virtual capacity, which is determined by the credit in the trading account of the wind power producer.

B. Structure of Bi-level Stochastic Optimization Model

The optimal trading strategy of the wind power producer with virtual bidding is obtained by solving a bi-level stochastic optimization problem, which consists of an upper-level problem and a lower-level problem, as illustrated in Fig. 2. The upper-level problem is established to maximize the expected total profit of the wind power producer obtained from the wind power and virtual bidding, and the lower-level problem is established to maximize the total social welfare in the DA market for the market operator, which considers the impact of wind power and virtual bidding on the clearing outcomes of the DA market.

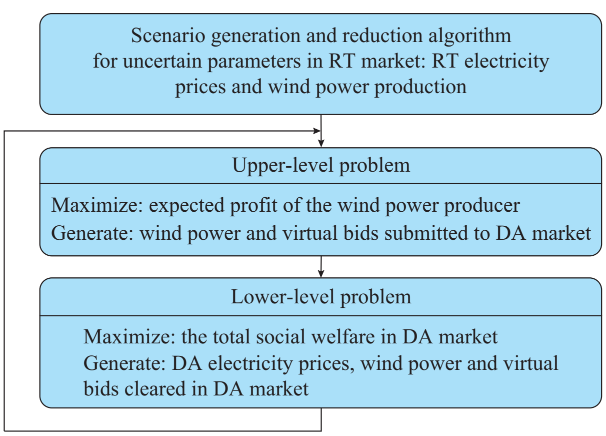

Fig. 2. Structure of bi-level stochastic optimization model.

Since the wind power producer using virtual bidding studied in this paper can influence the DA market outcomes by submitting its DA wind power and virtual bids strategically, it is considered as a price-maker in the DA electricity market. However, the wind power producer cannot behave strategically to change its wind power and virtual trading quantities in the RT electricity market because its RT power deviations are inelastic and have to be settled at the RT electricity price in the RT power trading floor. Thus, the impact of the wind power producer's trading strategy on the RT electricity prices is much lower than other RT market players with flexible resources. Hence, the wind power producer using virtual bidding is considered as a price-taker in the RT electricity market, which is similar to the model assumptions adopted in [1], [5], and [6].

Two uncertain parameters of the bi-level stochastic optimization problem, i.e., the RT electricity price and actual wind power production, are represented by scenarios, which are generated by the seasonal autoregressive integrated moving average (SARIMA) models [27]. To characterize the uncertain parameters accurately, the scenario sets generated by the SARIMA models are usually large, which may render the corresponding stochastic optimization problem intractable. To solve this issue, the fast forward scenario reduction algorithm given in [28] is applied to reduce the number of scenarios for each uncertain parameter without losing much information of the original scenario set. The scenario generation and reduction are executed before solving the bi-level optimization problem, as shown in Fig. 2.

III. Model Formulation

A. Upper-level Problem

The upper-level problem maximizes the total expected profits of the wind power and virtual bidding in the two-settlement electricity market and is expressed as:

$$\max_{\Xi}\,(1-\beta)\sum_{t=1}^{T}\sum_{w=1}^{\Omega}\pi_w\Bigg[\sum_{i=1}^{I}\sum_{p=1}^{P}\lambda^{DA}_{(n:i\in\psi^I_n)tw}P^{WD}_{pitw}+\sum_{i=1}^{I}\lambda^{RT}_{(n:i\in\psi^I_n)tw}\left(P^{WR}_{itw}-\sum_{p=1}^{P}P^{WD}_{pitw}\right)+\sum_{v=1}^{V}\left(\lambda^{DA}_{(n:v\in\psi^V_n)tw}-\lambda^{RT}_{(n:v\in\psi^V_n)tw}\right)\left(P^{VI}_{vtw}-P^{VD}_{vtw}\right)\Bigg]+\beta\left(\zeta-\frac{1}{1-\alpha}\sum_{w=1}^{\Omega}\pi_w\eta_w\right) \tag{1}$$

s.t.

$$0\le\lambda^{WD}_{pit}\le\lambda^{CapD}\quad\forall p,\forall i,\forall t \tag{2}$$

$$0\le\lambda^{VI}_{vt}\le\lambda^{CapD}\quad\forall v,\forall t \tag{3}$$

$$0\le\lambda^{VD}_{vt}\le\lambda^{CapD}\quad\forall v,\forall t \tag{4}$$

$$\sum_{p=1}^{P}P^{WD,\max}_{pit}\le P^{W,\max}_{i}\quad\forall i,\forall t \tag{5}$$

$$\sum_{v=1}^{V}\left(P^{VI,\max}_{vt}+P^{VD,\max}_{vt}\right)\le P^{V,\max}\quad\forall v,\forall t \tag{6}$$

$$0\le P^{VI,\max}_{vt}\le M_{vt}z_{vt}\quad\forall v,\forall t \tag{7}$$

$$0\le P^{VD,\max}_{vt}\le M_{vt}\left(1-z_{vt}\right)\quad\forall v,\forall t \tag{8}$$

$$z_{vt}\in\{0,1\}\quad\forall v,\forall t \tag{9}$$

$$\eta_w\ge 0\quad\forall w \tag{10}$$

$$\zeta-\eta_w\le\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{p=1}^{P}\lambda^{DA}_{(n:i\in\psi^I_n)tw}P^{WD}_{bitw}+\sum_{t=1}^{T}\sum_{i=1}^{I}\lambda^{RT}_{(n:i\in\psi^I_n)tw}\left(P^{WR}_{itw}-\sum_{p=1}^{P}P^{WD}_{pitw}\right)+\sum_{t=1}^{T}\sum_{v=1}^{V}\left(\lambda^{DA}_{(n:v\in\psi^V_n)tw}-\lambda^{RT}_{(n:v\in\psi^V_n)tw}\right)\left(P^{VI}_{vtw}-P^{VD}_{vtw}\right)\quad\forall w \tag{11}$$

$$(A1)\text{-}(A22) \tag{12}$$

where $\Xi=\{\lambda_{pit}^{WD},\lambda_{vt}^{VI},\lambda_{vt}^{VD},P_{pit}^{WD,\max},P_{vt}^{VI,\max},P_{vt}^{VD,\max},\zeta,\eta_w,\Xi^D\}$ is the set of all decision variables in the upper-level and lower-level problems, and Ξ^D is the set of all the decision variables in the lower-level problem.

The objective function (1) maximizes the total expected profits of wind power and virtual bidding in the DA and RT markets multiplied by a weighting factor $1-\beta$ and the $CVaR_\alpha$ multiplied by a weighting factor β. In (1), $\lambda_{(n:i\in\psi_n^I)tw}^{DA}$, $\lambda_{(n:v\in\psi_n^V)tw}^{DA}$, P_{pitw}^{WD}, P_{vtw}^{VI}, and P_{vtw}^{VD} are the variables determined in the lower-level problem, as shown in (A1)-(A22). Constraints (2)-(4) limit the DA bidding prices of the wind and virtual units to the price cap specified by the market. Constraints (5) and (6) limit the bidding quantities of the wind and virtual units to their maximum capacities, respectively. Constraints (7)-(9) ensure either an incremental or a decremental virtual bid is generated at each bus. Constraints (10) and (11) are used to compute the conditional value at risk (CVaR), which is used as a measurement of risk in this paper. The $CVaR_\alpha$ is computed as the expected value measurement of the $(1-\alpha)\times 100\%$ least profitable scenarios [29]. The parameter β reflects the risk aversion level of the wind power producer using virtual bidding, and a higher value of β indicates that the optimal bidding strategy is more risk averse. Constraints (A1)-(A22) indicate the upper-level problem is subject to the lower-level problem provided in Section III-B.

B. Lower-level Problem

The lower-level problem models the clearing process of the DA market for each scenario w and is formulated as:

$$\min_{\Xi^D}\left(\sum_{i=1}^{I}\sum_{p=1}^{P}\lambda_{pit}^{WD}P_{pitw}^{WD}+\sum_{v=1}^{V}\lambda_{vt}^{VI}P_{vtw}^{VI}-\sum_{v=1}^{V}\lambda_{vt}^{VD}P_{vtw}^{VD}+\sum_{j=1}^{J}\sum_{b=1}^{B}\lambda_{bjt}^{CD}P_{bjtw}^{CD}-\sum_{l=1}^{D}\sum_{e=1}^{E}\lambda_{elt}^{LD}P_{eltw}^{LD}\right) \tag{13}$$

s.t.

$$\sum_{i\in\psi_m^I}\sum_{p=1}^{P}P_{pitw}^{WD}+\sum_{j\in\psi_n^J}\sum_{b=1}^{B}P_{bjtw}^{CD}+\sum_{v\in\psi_n^V}P_{vtw}^{VI}-\sum_{v\in\psi_n^V}P_{vtw}^{VD}-\sum_{l\in\psi_n^L}\sum_{e=1}^{E}P_{eltw}^{LD}-\sum_{k|s(k)=n}f_{ktw}^{D}+\sum_{k|r(k)=n}f_{ktw}^{D}=0:\ \lambda_{ntw}^{DA}\quad \forall n,\forall t,\forall w \tag{14}$$

$$f_{ktw}^{D}=B_k\left(\delta_{s(k)tw}^{DA}-\delta_{r(k)tw}^{DA}\right):\ \Phi_{ktw}\quad \forall k,\forall t,\forall w \tag{15}$$

$$-C_k^{\max}\le f_{ktw}^{D}\le C_k^{\max}:\ \Phi_{ktw}^{D,\max},\Phi_{ktw}^{D,\min}\quad \forall k,\forall t,\forall w \tag{16}$$

$$0\le P_{pitw}^{WD}\le P_{pit}^{WD,\max}:\ \mu_{pitw}^{WD,\max},\mu_{pitw}^{WD,\min}\quad \forall p,\forall i,\forall t,\forall w \tag{17}$$

$$0\le P_{vtw}^{VI}\le P_{vt}^{VI,\max}:\ \mu_{vtw}^{VI,\max},\mu_{vtw}^{VI,\min}\quad \forall v,\forall t,\forall w \tag{18}$$

$$0\le P_{vtw}^{VD}\le P_{vt}^{VD,\max}:\ \mu_{vtw}^{VD,\max},\mu_{vtw}^{VD,\min}\quad \forall v,\forall t,\forall w \tag{19}$$

$$0\le P_{bjtw}^{CD}\le P_{bjt}^{CD,\max}:\ \mu_{bjtw}^{CD,\max},\mu_{bjtw}^{CD,\min}\quad \forall b,\forall j,\forall t,\forall w \tag{20}$$

$$0\le P_{eltw}^{LD}\le P_{elt}^{LD,\max}:\ \mu_{eltw}^{LD,\max},\mu_{eltw}^{LD,\min}\quad \forall e,\forall l,\forall t,\forall w \tag{21}$$

$$-\pi\le\delta_{ntw}^{DA}\le\pi:\ \theta_{ntw}^{D,\max},\theta_{ntw}^{D,\min}\quad \forall n\ge 2,\forall t,\forall w \tag{22}$$

$$\delta_{ntw}^{DA}=0:\ \theta_{ntw}^{D1}\quad n=1,\forall t,\forall w \tag{23}$$

where $\Xi^D=\{P_{pitw}^{WD},P_{vtw}^{VI},P_{vtw}^{VD},P_{bjtw}^{CD},P_{eltw}^{LD},\lambda_{ntw}^{DA},\Phi_{ktw},\Phi_{ktw}^{D,\min},\Phi_{ktw}^{D,\max},\mu_{pitw}^{WD,\max},\mu_{pitw}^{WD,\min},\mu_{vtw}^{V,\max},\mu_{vtw}^{V,\min},\mu_{bjtw}^{CD,\max},\mu_{bjtw}^{CD,\min},\mu_{eltw}^{LD,\max},\mu_{eltw}^{LD,\min},\theta_{ntw}^{D,\max},\theta_{ntw}^{D,\min},\theta_{ntw}^{D1}\}$. The set Ξ^D includes both the primal and dual variables, and the dual variables are provided after the colons in the constraints.

The objective function (13) minimizes the negative expected total social welfare in each time period and each scenario. Constraint (14) enforces the DA power balance at each bus considering virtual bids. Constraint (15) is the power flow equation of each transmission line. Constraint (16) provides the capacity limits of each transmission line. Constraints (17)-(21) represent the bounds of wind, virtual, and conventional units and demands. Constraints (22) and (23) present the voltage angle limits for each bus, where $n=1$ indicates the first bus is selected as the reference bus of the power system.

C. Solution Method

The proposed bi-level stochastic optimization problem (1)-(23) can be transferred into an equivalent single-level stochastic mathematical program with equilibrium constraints (MPEC) model through the Karush-Kuhn-Tucker (KKT) conditions of the lower-level problem (13)-(23) presented in Appendix A [30]. This single-level stochastic MPEC model includes (1)-(12) and (A1)-(A22).

The objective function and constraints of the single-level stochastic MPEC model contains nonlinear terms, which can be linearized by using the duality theory and the big-M method, respectively. The details are provided in Appendix B. As a result, the stochastic MPEC model is converted to be a mixed-integer linear programming (MILP) problem that can be solved by existing commercial solvers directly.

The computational cost of solving the stochastic MPEC model depends on the numbers of decision variables and constraints. Since the buses used for virtual bidding are not limited to those with power plants or demands, the wind power producer is assumed to have a virtual unit at each bus of the power network. Thus, the virtual unit number V is equal to the bus number N of the power network. In this circumstance, both the decision variables and constraints related to virtual bidding in the stochastic MPEC model increase with the bus number N. To reduce the computational cost of solving the stochastic MPEC model for large power systems, a method of reducing the number of buses considered for virtual bidding is proposed in Section III-D.

D. Method of Reducing Number of Buses Considered for Virtual Bidding

In practice, since the wind power producer has limited credit in its trading account, it would only submit DA virtual bids at a small number of buses of the power network. Thus, if the buses that are unlikely used for virtual bidding are identified and then eliminated from being considered for virtual bidding before solving the stochastic MPEC model, the model could be simplified so that the computational cost of solving the model would be reduced. Therefore, this subsection proposes a method of reducing the number of buses considered for virtual bidding for identifying and eliminating the buses that are unlikely to be used for virtual bidding, which is presented below.

Step 1: the stochastic MPEC model is decomposed into Ω independent deterministic MPEC models, denoted as DM_w ($w=1,2,\ldots,\Omega$), by considering the Ω different scenarios, respectively. Each deterministic MPEC model DM_w consists of the objective function (1) with $\beta=0$ as well as the constraints (2)-(9) and (A1)-(A22), where the uncertain parameters in DM_w are represented by their values in the scenario w.

Step 2: the Ω independent deterministic MPEC models DM_w are solved separately by using the solution method proposed in Section III-C, from which the buses with virtual bids in DM_w are identified as the buses that are likely used for virtual bidding in the stochastic MPEC model. Specifically, in each time period t, there are N_t^R buses with virtual bids in the deterministic MPEC models DM_w, which are more likely to be used for virtual bidding in the stochastic MPEC model than the other $N-N_t^R$ buses without virtual bids in DM_w. In this step, the computational cost of solving the Ω deterministic MPEC models DM_w separately is much lower than that of solving the stochastic MPEC model with Ω scenarios.

Step 3: the $N-N_t^R$ buses without virtual bids in DM_w ($w=1,2,\ldots,\Omega$) are eliminated from being considered for virtual bidding in the stochastic MPEC model. The resulting stochastic MPEC model with reduced N_t^R buses considered for virtual bidding is denoted as MPEC-R, which is solved by using the solution method proposed in Section III-C to generate the optimal bidding strategies for the wind power producer using virtual bidding.

In the simplified stochastic model MPEC-R, since the virtual bidding is only considered at the reduced N_t^R buses in each time period t, the number of virtual units is decreased significantly from N to N_t^R. As a consequence, both the decision variables and constraints related to virtual bidding in the MPEC-R are much less than those in the MPEC model. Thus, the computational cost of solving the MPEC-R to generate the optimal bidding strategies for the wind power producer is much lower than that of solving the MPEC model.

IV. Case Studies and Results

To validate the proposed stochastic optimization model for the wind power producer using virtual bidding, illustrative case studies are performed for a six-bus test system in Section IV-A to Section IV-D [31], and for the IEEE 118-bus test system in Section IV-E [32]. The historical wind power data are obtained from the National Renewable Energy Laboratory (NREL) website [33]. The data of historical RT electricity price are obtained from the PJM electricity market website [34]. The default value of the risk aversion parameter is set to be zero, and the parameters used in each case study are provided in the corresponding subsection. The proposed MILP problem is solved by using YALMIP [35] and Gurobi 7.0 in MATLAB [36]. The computer used for simulation studies has a 3.50 GHz, 4-core CPU and 32 GB RAM.

A. Deterministic MPEC Model Without Transmission Constraints

As shown in Fig. 3, the six-bus test system consists of eight generating units P1-P8 and four demands D1-D4, where P1 is the wind unit of the strategic wind power producer and P2-P8 are the conventional generation units of other power producers. The data of P2-P8 are provided in Table I. The installed capacity of the wind unit is 250 MW, which is about 21% of the total installed generation capacity of the system. The DA demand bidding quantities of D1-D4 are constant in 24 hours of a day, which are provided in Table II. While the demand bidding prices of D1-D4 are different in 24 hours of a day, which are provided in Table III. The deterministic MPEC model with a single scenario described in Section III-D is firstly studied, in which the values of the uncertain parameters are represented by their forecasting values. Moreover, no capacity limits are imposed on the transmission lines. Therefore, there are no constraints in the deterministic MPEC model. The wind power and virtual capacities are both set to be 250 MW.

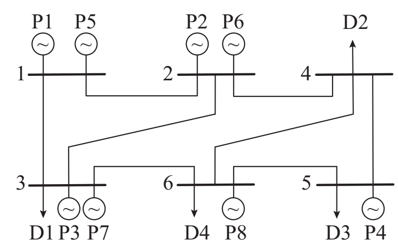

Fig. 3. Six-bus test system.

TABLE I
Data of Conventional Generation Units

Unit	Maximum offer capacity (MW)				Generation offer price ($/MWh)			
	$P_{1j}^{CD,\max}$	$P_{2j}^{CD,\max}$	$P_{3j}^{CD,\max}$	$P_{4j}^{CD,\max}$	λ_{1j}^{CD}	λ_{2j}^{CD}	λ_{3j}^{CD}	λ_{4j}^{CD}
P2	15.80	0.20	3.8	0.2	14.47	14.85	20.88	21.11
P3	15.00	15.00	10.0	10.0	0	0	0	0
P4	140.00	97.50	52.5	70.0	24.96	26.42	27.59	28.77
P5	2.40	3.40	3.6	2.4	30.43	30.91	34.89	39.52
P6	68.90	49.25	39.4	39.4	13.10	13.86	14.42	15.24
P7	76.00	15.20	22.8	15.2	14.90	15.55	18.06	20.76
P8	54.25	38.75	31.0	31.0	12.90	13.33	13.88	14.64

TABLE II
Data of DA Demand Bidding Quantities in Six-bus Test System

Unit	Demand bidding quantity (MW)				
	$P_{1l}^{LD,\max}$	$P_{2l}^{LD,\max}$	$P_{3l}^{LD,\max}$	$P_{4l}^{LD,\max}$	$P_{5l}^{LD,\max}$
D1	136.8	3.8	3.8	3.8	3.8
D2	194.4	5.4	5.4	5.4	5.4
D3	194.4	5.4	5.4	5.4	5.4
D4	194.4	5.4	5.4	5.4	5.4

The electricity prices and wind power generation as well as the profits of one day obtained by solving the deterministic optimization problem are shown in Figs. 4 and 5, respectively. The profit of wind power bidding depends on electricity prices and wind power generation; while the profit of virtual bidding depends on the price differences between the DA and RT markets, because the virtual capacity is a fixed value determined by the credit of the wind power producer in the trading account. As shown in Figs. 4 and 5, the maximum profit of the wind power bidding occurs in the 20th hour, because both the wind power generation and RT price are high in this hour. The maximum profit of the virtual bidding occurs in the 6th hour during which the price difference between the DA and RT markets is the highest among the 24 hours. In most hours, the profit of the wind power bidding is much higher than that of the virtual bidding, because the DA and RT electricity prices are much higher than their difference.

TABLE III
DATA OF DA DEMAND BIDDING PRICES IN SIX-BUS TEST SYSTEM

t (hour)	Demand bidding price ($/MWh)				
	λ_{1lt}^{LD}	λ_{2lt}^{LD}	λ_{3lt}^{LD}	λ_{4lt}^{LD}	λ_{5lt}^{LD}
1	22.66	22.43	22.38	21.95	21.83
2	22.43	22.38	21.95	21.83	21.29
3	22.38	21.95	21.83	21.29	21.22
4	22.38	21.95	21.83	21.29	21.22
5	21.95	21.83	21.29	21.22	20.97
6	21.95	21.83	21.29	21.22	20.97
7	22.43	22.38	21.95	21.83	21.29
8	23.32	22.90	22.66	22.43	22.38
9	25.00	24.61	24.45	23.85	23.60
10	26.49	25.90	25.39	25.00	24.61
11	32.46	29.42	27.14	26.79	26.49
12	32.50	32.46	29.42	27.14	26.79
13	32.50	32.46	29.42	27.14	26.79
14	32.46	29.42	27.14	26.79	26.49
15	26.49	25.90	25.39	25.00	24.61
16	26.49	25.90	25.39	25.00	24.61
17	27.14	26.79	26.49	25.90	25.39
18	32.50	32.46	29.42	27.14	26.79
19	32.50	32.46	29.42	27.14	26.79
20	32.50	32.46	29.42	27.14	26.79
21	32.50	32.46	29.42	27.14	26.79
22	32.46	29.42	27.14	26.79	26.49
23	25.39	25.00	24.61	24.45	23.85
24	23.32	22.90	22.66	22.43	22.38

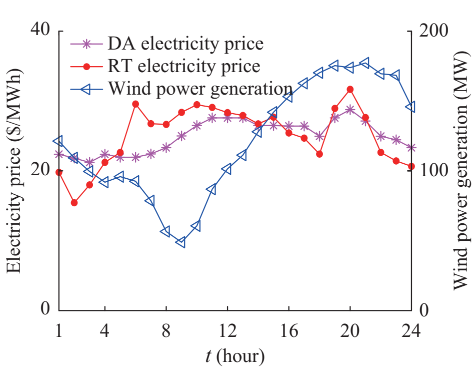

Fig. 4. Electricity prices and wind power generation in different time periods of a day.

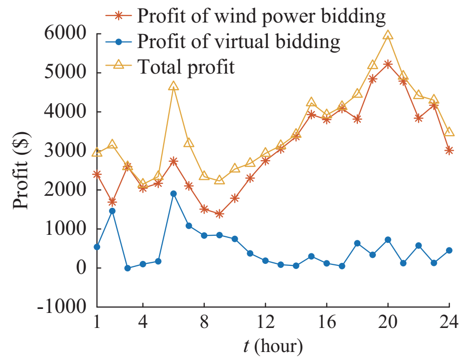

Fig. 5. Profits in different time periods of a day.

B. Impacts of Transmission Constraints, Wind Unit Location, and Wind and Virtual Capacities

In the second case study, the transmission constraints (A19) and (A20) are added to the deterministic MPEC model DM_w in Section IV-A. The wind and virtual capacities are changed from 0 to 400 MW with an increment of 50 MW to study their impacts on the total profit of the wind power producer and the average price difference between the DA and RT markets. Considering the transmission constraints and the location of the wind unit, the simulations are carried out in three different cases.

1) Case 1: no capacity limits are imposed on the transmission lines and the wind unit is at bus 1.

2) Case 2: the capacity limit of transmission line is 100 MW and the wind unit is at bus 1.

3) Case 3: the capacity limit of transmission line is 100 MW and the wind unit is at bus 4.

The other parameters are set to be the same as those used in Section IV-A. The results of the total profit of the wind power producer and the average price difference between the DA and RT markets in Cases 1-3 are shown in Figs. 6 and 7, respectively.

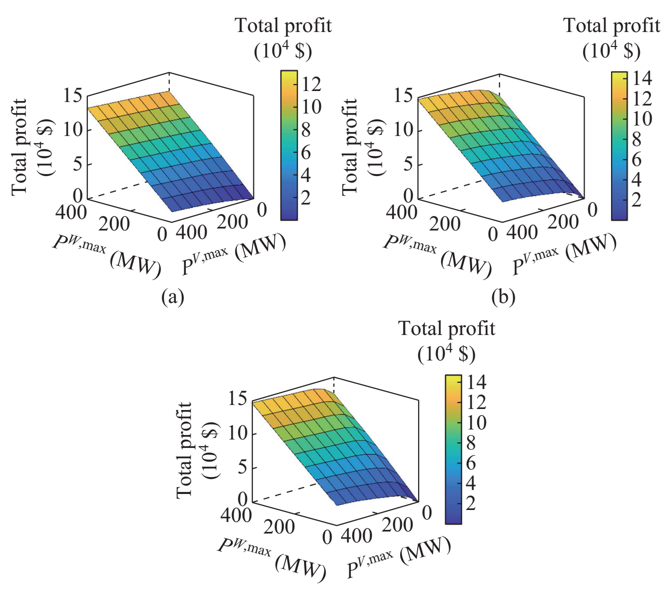

Fig. 6. Total profit of wind power producer in different cases. (a) Case 1. (b) Case 2. (c) Case 3.

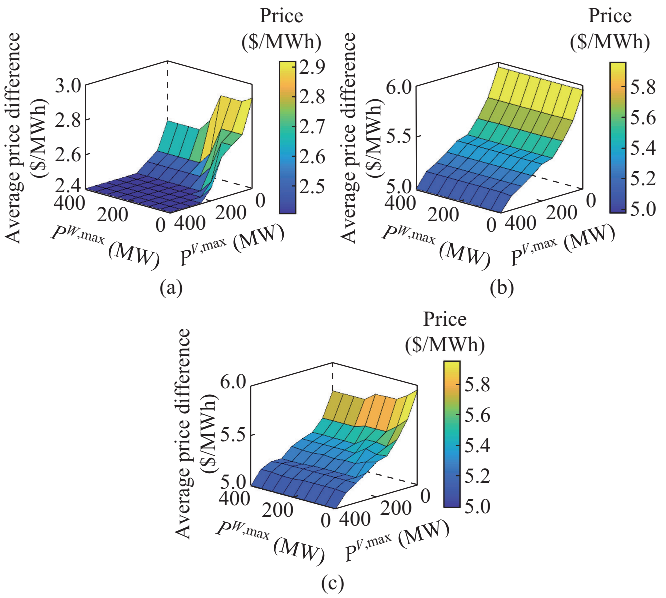

Fig. 7. Average price difference between DA and RT markets in different cases. (a) Case 1. (b) Case 2. (c) Case 3.

As shown in Fig. 6, the total profit increases with virtual and wind capacities. However, the results of the three cases are different due to different transmission limits and/or wind unit locations. When the wind capacity is 0, Cases 2 and 3 are the same and the model is used by a financial participant, and the maximum total profits of the virtual bidding in Cases 1-3 are \$15715, \$29879, and \$29879, respectively. The virtual bidding brings more profits in Cases 2 and 3 because the transmission limits lead to the network congestion and higher price differences. Moreover, the wind power producer can use virtual bidding to obtain more profits when the power network is more likely to congest, as in Cases 2 and 3.

The impacts of wind and virtual capacities on the average price differences between the DA and RT markets are different in the three cases. As shown in Fig. 7(a), when there is no transmission limit, both the virtual and wind capacities affect the average price difference. However, the average price difference in Fig. 7(b) almost does not change with the wind capacity, which shows that the market power of the wind unit located at bus 1 is limited due to the network congestion. However, when the wind unit is located at bus 4 in Case 3, the average price difference changes with the wind capacity and the network congestion does not limit the market power of wind unit so significantly as that in Case 2. For instance, in Fig. 7(c), when the virtual capacity is 50 MW and the wind capacity is increased from 0 to 100 MW, the average price difference is decreased by 3.15%. Additionally, when the virtual and wind capacities are very large in an uncongested network, a further increase of the wind or virtual capacity will have little impact on the average price difference, meaning that the wind and virtual units will have little additional market power. As shown in Fig. 7(a), when the virtual capacity is 200 MW and the wind capacity is increased from 100 MW to 200 MW, the average price difference is unchanged.

Therefore, if a wind power producer expects to improve its profit by increasing the wind or virtual capacity, both the transmission limits and wind unit location should be considered in the decision-making process; and it would be better to conduct detailed simulations to estimate the potential economic benefits of increasing the wind or virtual capacity beforehand.

C. Stochastic MPEC Model with Risk Management

In the third case study, the complete stochastic MPEC model is studied, where CVaR is used for risk management; and the wind and virtual capacities are both set to be 250 MW. Five hundred scenarios are first generated for each uncertain parameter based on the SARIMA model and are then reduced to eight. Since two uncertain parameters are considered in the model, the total scenario number used in the stochastic optimization problem is 64. The risk aversion parameter β is changed from 0 to 0.9 with an increment of 0.15 to study its impact on the expected profit and CVaR. The other model parameters are set to be the same as those used in Case 2 of Section IV-B. Figure 8 shows the simulation results of the Cases 1-3 with different β values.

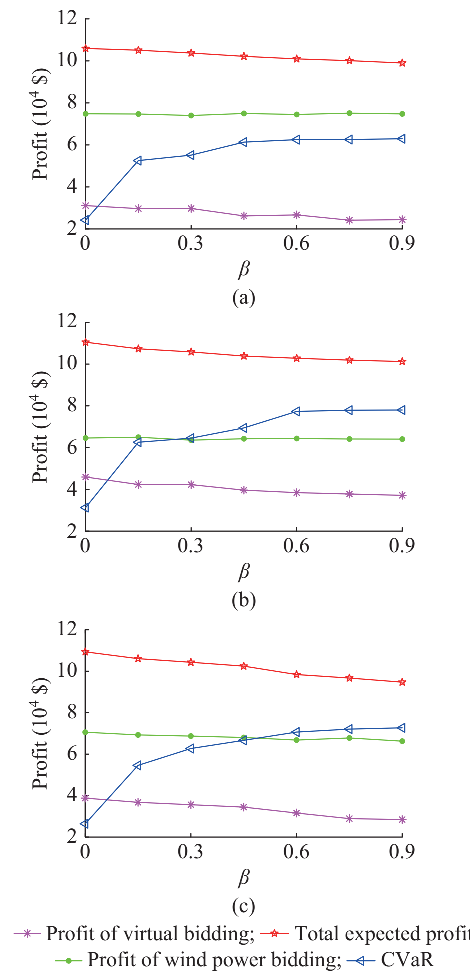

Fig. 8. Impact of risk aversion degree on simulation results in Cases 1-3. (a) Case 1. (b) Case 2. (c) Case 3.

As shown in Fig. 8, when β increases, the total expected profit decreases and the CVaR increases, respectively. This means that a larger β leads to less total expected profit but a smaller risk. It should be noted that when β is changed from 0 to 0.15, the total expected profits of the three cases only decrease slightly by about 0.79%, 2.87%, and 3.01%, respectively, but the CVaR increases significantly by about 116.9%, 100.04%, and 106.5%, respectively. The results show that, compared with the risk-neutral trading strategy, even a small risk aversion parameter can significantly improve the expected profits of the worst scenarios. However, when β is larger than 0.15, increasing its value cannot significantly improve the CVaR. The results indicate that choosing a small value for β, such as 0.15, would be appropriate for the proposed optimization problem, which could significantly reduce the risk without decreasing the expected profit too much.

In Cases 1 and 2, when β is changed from 0 to 0.9, the profits of virtual bidding decrease by about 22.31% and 20.02%, respectively, but the profits brought by wind power bidding only decrease by about 0.14% and 0.81%, respectively. When the wind unit is at bus 1, the virtual bidding strategy is much more sensitive to the risk aversion parameter than the wind power bidding strategy, because virtual bidding can be used at multiple buses; while wind power bidding is limited due to the power network congestion. However, when the wind unit is at bus 4, it becomes more sensitive to the risk aversion parameter. In Case 3, when β is changed from 0 to 0.9, the profit of wind power bidding decreases by about 5.91%, which is much larger than that in Case 2. This means that the wind power bidding is not so limited by the congestion when the wind unit is at bus 4.

Therefore, the risk management for the wind power producer using virtual bidding is related to transmission constraints and the wind unit location, and the risk aversion parameter should be chosen carefully considering the impacts of transmission constraints and wind unit locations.

D. Impact of Wind Power Volatility

In this subsection, the impact of wind power volatility on the results of the stochastic MPEC model is investigated. Except for the scenario values of the wind power production, the other model parameters are set to be the same as those used in Section IV-C. For the wind unit, in the time period t, the wind power scenarios generated by the SARIMA model follow a normal distribution $N(P_{it}^{WF}, \sigma_{it}^2)$. To simulate different levels of wind power volatility, the value of σ_{it} is multiplied by an adjustable wind volatility coefficient λ. When λ is zero, the wind power production is assumed to be deterministic, which can be forecasted accurately. When λ is larger, the value of σ_{it} is assumed to be larger, and the wind power scenarios generated by the SARIMA model are more volatile.

By solving the stochastic MPEC model with different wind volatility coefficients, the simulation results under different wind power volatility conditions are obtained, and the total expected profit of the wind power producer and total expected social welfare of the DA market are shown in Figs. 9 and 10, respectively. When the wind power is more volatile and more difficult to be forecasted, both the total expected profit of the wind power producer and the total expected social welfare of the DA market decrease. For instance, when the maximum virtual capacity is 0 and λ is changed from 0 to 1.5, the total expected profit of the wind power producer and the total expected social welfare of the DA market decrease by 7.76% and 18.35%, respectively. Additionally, as shown in Figs. 9 and 10, when virtual bidding is used by the wind power producer, both the total expected profit of the wind power producer and the total expected social welfare of the DA market increase, which indicates that the virtual bidding is beneficial to both the profitability of the wind power producer and the efficiency of the electricity market.

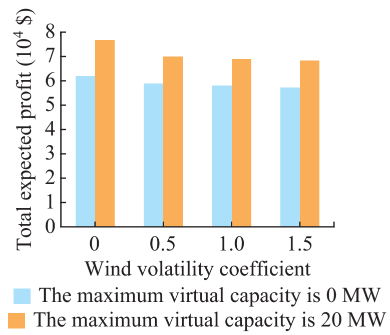

Fig. 9. Impact of wind power volatility on total expected profit of wind power producer.

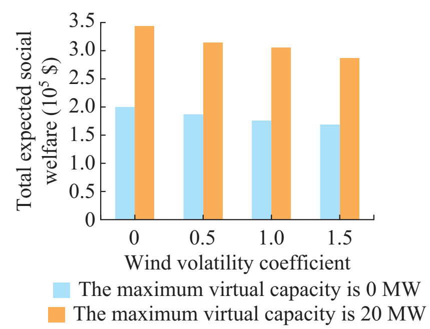

Fig. 10. Impact of wind power volatility on total expected social welfare of DA market.

E. Case Studies on IEEE 118-bus Test System

Case studies on the IEEE 118-bus test system are carried out to further verify the applicability of the proposed stochastic MPEC model for large systems. The wind unit is assumed to locate at bus 1. The maximum wind and virtual capacities of the wind power producer are both 250 MW. The DA market offers data of the other producers and the thermal limits of the transmission lines are provided in [32]. The DA demand bidding quantities in Table II and prices in Table III of D1-D4 are used in the IEEE 118-bus test system, where D1 is used at buses 11-14, D2 is used at buses 36-39, D3 is used at buses 61-64, and D4 is used at buses 86-89.

By solving the proposed stochastic MPEC model for the IEEE 118-bus test system, the DA wind power and virtual bidding strategies of a typical day are generated and provided in Table IV, where the virtual bids with positive and negative quantities are the incremental and decremental bids, respectively. The expected price differences between the DA and RT markets at the IEEE 118-bus test system are shown in Fig. 11. It shows that the incremental and decremental virtual bids are submitted at the buses with positive and negative price differences, respectively. From the 1st hour to the 5th hour, the wind power producer submits incremental virtual bids at bus 36, where the expected price differences between the DA and RT markets are positive. In contrast, from the 7th hour to the 10th hour, the wind power producer submits decremental virtual bids at buses 94, 19, 93, and 15, respectively, where the expected price differences between the DA and RT markets are negative.

TABLE IV
OPTIMAL DA WIND POWER AND VIRTUAL BIDS OF WIND POWER PRODUCER IN IEEE 118-BUS TEST SYSTEM

t (hour)	Wind power bid		Virtual bid		
	Quantity (MW)	Price ($/MWh)	Quantity (MW)	Price ($/MWh)	Bus No.
1	200.2	22.7	250	0	36
2	200.2	22.4	250	0	36
3	200.2	22.4	250	0	36
4	200.2	22.4	250	0	36
5	200.2	21.9	250	0	36
6	203.3	21.9	–250	21.9	19
7	250.0	22.4	–250	22.4	94
8	203.4	23.3	–250	23.3	19
9	201.2	25.0	–250	25.0	93
10	204.8	26.5	–250	26.5	15
11	198.5	32.5	250	0	36
12	198.5	32.5	250	0	36
13	198.5	32.5	250	0	36
14	198.5	32.5	250	0	36
15	200.2	26.5	250	0	36
16	200.2	26.5	250	0	36
17	200.2	27.1	250	0	36
18	198.4	32.5	250	0	36
19	198.4	32.5	250	0	36
20	198.4	32.5	250	0	36
21	200.1	32.5	250	32.5	33
22	198.5	0	250	0	36
23	200.8	25.4	250	25.4	33
24	200.2	23.3	250	0	36

Next, the effectiveness of the proposed method of reducing the number of buses considered for virtual bidding is verified by utilizing the IEEE 118-bus test system. The decomposed deterministic models DM_w ($w=1,2,\ldots,64$) based on 64 scenarios are established and solved. Table V shows the virtual bidding buses over the 24 hours obtained by solving DM_w ($w=1,2,\ldots,64$), which include all of the optimal virtual bidding buses in Table IV obtained by solving the stochastic MPEC model. Then, the stochastic MPEC model is simplified to be the MPEC-R that only considers the buses identified in Table V for virtual bidding. The simulation results obtained by solving the MPEC model and the MPEC-R are compared in Table VI. It shows that the total expected profits obtained by solving the two models are the same. Compared with the MPEC model, the decision variables and constraints of the simplified MPEC-R model are reduced by about 19.63% and 35.61%, respectively, which reduce the computational cost of solving the MPEC-R by about 73.28%.

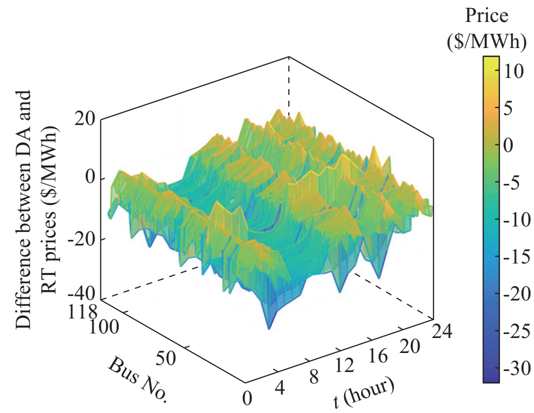

Fig. 11. Expected differences between DA and RT electricity prices at different buses of IEEE 118-bus test system.

TABLE V
VIRTUAL BIDDING BUSES OBTAINED BY SOLVING DM_w ($w=1,2,\ldots,64$)

t (hour)	Bus No.
1	15, 19, 24, 33, 36, 107
2	15, 24, 33, 36, 107
3	15, 19, 33, 36, 59, 107
4	15, 24, 19, 33, 36, 107
5	15, 19, 33, 36, 86, 107
6	15, 19, 33, 107
7	15, 19, 24, 33, 94, 107
8	15, 19, 33, 94, 107
9	15, 19, 33, 41, 93, 107
10	15, 19, 33, 36, 41, 86, 94, 107
11	15, 41, 33, 36, 86, 107
12	15, 19, 33, 36, 86, 107
13	15, 19, 33, 36, 86, 107
14	15, 19, 33, 36, 107
15	15, 19, 33, 36, 107
16	15, 19, 33, 36, 107
17	15, 19, 33, 36, 107
18	15, 24, 33, 36, 107
19	15, 19, 33, 36, 59, 107
20	19, 33, 36, 86, 107
21	15, 19, 33, 36, 51, 59, 77, 86, 107
22	15, 33, 36, 59, 107
23	15, 33, 36, 41, 59, 107
24	15, 33, 36, 41, 107

TABLE VI
SIMULATION RESULTS OBTAINED BY SOLVING MPEC MODEL AND MPEC-R

Type of model	Number of decision variables	Number of constraints	Computational cost (s)	Total expected profit ($)
MPEC	5332080	12662496	1074	190906
MPEC-R	4285644	8153112	287	190906

V. Conclusion

This paper proposes a bi-level stochastic optimization model for generating the bidding strategies for a price-maker wind power producer, which is used to improve the market power of wind power producers in the DA market by submitting the incremental and decremental virtual bids at multiple buses. By using the KKT conditions, duality theory, and big-M method, the bi-level nonlinear problem is converted into a single-level MILP problem, which can be solved by commercial solvers. To reduce the computational cost of solving the proposed stochastic model for large systems, a method of reducing the number of buses considered for virtual bidding is proposed to simplify the model by reducing its decision variables and constraints related to virtual bidding.

Case studies are carried out for a wind power producer using virtual bidding. The results have shown that the virtual bidding can improve the profit of the wind power producer due to its increased trading volume in the DA and RT markets, and the proposed method of reducing the number of buses considered for virtual bidding can significantly reduce the computational cost of solving the proposed stochastic model. The transmission limits, wind unit location, risk aversion parameter, wind power volatility, and wind and virtual capacities could affect the proposed trading strategy significantly. Therefore, it is recommended that wind power producers using virtual bidding should carry out detailed simulation studies beforehand to estimate the potential benefits and risks caused by these factors. Moreover, by using the proposed model, market operators can analyze the virtual bidding used by price-maker physical participants in detail and, therefore, help themselves make better rules and policies for the related market activities.

The future research will consider using other other optimization techniques, physical assets, and power trading floors for strategic wind power producers with virtual bidding to improve their profits and reduce their risks. For instance, the wind power producer could utilize robust chance constraints [37] and stochastic dominance constraints [38] to reduce the risks associated with DA and RT electricity prices, and could also utilize demand-side resources [39] or battery storage [40] to mitigate the power deviations caused by volatile wind power productions. Additionally, when there are multiple strategic electricity market participants using virtual bidding, equilibrium models could be utilized to model and analyze their competition in the market, which might be of interest to the electricity market operators or policy makers.

Appendix A

The KKT conditions of (13)-(23) are given as:

$$\lambda_{pit}^{WD}-\lambda_{ntw}^{DA}+\mu_{pitw}^{WD,\max}-\mu_{pitw}^{WD,\min}=0 \quad \forall p,i\in\psi_n^I,\forall t,\forall w \tag{A1}$$

$$\lambda_{vt}^{VI}-\lambda_{ntw}^{DA}+\mu_{vtw}^{VI,\max}-\mu_{vtw}^{VI,\min}=0 \quad \forall v\in\psi_n^V,\forall t,\forall w \tag{A2}$$

$$-\lambda_{vt}^{VD}+\lambda_{ntw}^{DA}+\mu_{vtw}^{VD,\max}-\mu_{vtw}^{VD,\min}=0 \quad \forall v\in\psi_n^V,\forall t,\forall w \tag{A3}$$

$$\lambda_{bjtw}^{CD}-\lambda_{ntw}^{DA}+\mu_{bjtw}^{CD,\max}-\mu_{bjtw}^{CD,\min}=0 \quad \forall b,j\in\psi_n^J,\forall t,\forall w \tag{A4}$$

$$-\lambda_{eltw}^{LD}+\lambda_{ntw}^{DA}+\mu_{eltw}^{LD,\max}-\mu_{eltw}^{LD,\min}=0 \quad \forall e,l\in\psi_n^L,\forall t,\forall w \tag{A5}$$

$$\lambda_{s(k)tw}^{DA}-\lambda_{r(k)tw}^{DA}-\Phi_{ktw}+\Phi_{ktw}^{D,\max}-\Phi_{ktw}^{D,\min}=0 \quad \forall k,\forall t,\forall w \tag{A6}$$

$$\sum_{k|s(k)=n}B_k\Phi_{ktw}-\sum_{k|r(k)=n}B_k\Phi_{ktw}+\theta_{ntw}^{D,\max}-\theta_{ntw}^{D,\min}=0 \quad \forall n\ge 2,\forall t,\forall w \tag{A7}$$

$$\sum_{k|s(k)=n}B_k\Phi_{ktw}-\sum_{k|r(k)=n}B_k\Phi_{ktw}-\theta_{ntw}^{D1}=0 \quad n=1,\forall t,\forall w \tag{A8}$$

$$0\le\left(P_{pit}^{WD,\max}-P_{pitw}^{WD}\right)\perp\mu_{pitw}^{WD,\max}\ge 0 \quad \forall p,\forall i,\forall t,\forall w \tag{A9}$$

$$0\le P_{pitw}^{WD}\perp\mu_{pitw}^{WD,\min}\ge 0 \quad \forall p,\forall i,\forall t,\forall w \tag{A10}$$

$$0\le\left(P_{vt}^{VI,\max}-P_{vtw}^{VI}\right)\perp\mu_{vtw}^{VI,\max}\ge 0 \quad \forall v,\forall t,\forall w \tag{A11}$$

$$0\le P_{vtw}^{VI}\perp\mu_{vtw}^{VI,\min}\ge 0 \quad \forall v,\forall t,\forall w \tag{A12}$$

$$0\le\left(P_{vt}^{VD,\max}-P_{vtw}^{VD}\right)\perp\mu_{vtw}^{VD,\max}\ge 0 \quad \forall v,\forall t,\forall w \tag{A13}$$

$$0\le P_{vtw}^{VD}\perp\mu_{vtw}^{VD,\min}\ge 0 \quad \forall v,\forall t,\forall w \tag{A14}$$

$$0\le\left(P_{bjt}^{CD,\max}-P_{bjtw}^{CD}\right)\perp\mu_{bjtw}^{CD,\max}\ge 0 \quad \forall b,\forall j,\forall t,\forall w \tag{A15}$$

$$0\le P_{bjtw}^{CD}\perp\mu_{bjtw}^{CD,\min}\ge 0 \quad \forall b,\forall j,\forall t,\forall w \tag{A16}$$

$$0\le\left(P_{elt}^{LD,\max}-P_{eltw}^{LD}\right)\perp\mu_{eltw}^{LD,\max}\ge 0 \quad \forall e,\forall l,\forall t,\forall w \tag{A17}$$

$$0\le P_{eltw}^{LD}\perp\mu_{eltw}^{LD,\min}\ge 0 \quad \forall e,l,t,w \tag{A18}$$

$$0\le\left(C_k^{\max}-f_{ktw}^{D}\right)\perp\Phi_{ktw}^{D,\max}\ge 0 \quad \forall k,t,w \tag{A19}$$

$$0\le\left(C_k^{\max}+f_{ktw}^{D}\right)\perp\Phi_{ktw}^{D,\min}\ge 0 \quad \forall k,t,w \tag{A20}$$

$$0\le\left(\pi-\delta_{ntw}^{DA}\right)\perp\theta_{ntw}^{D,\max}\ge 0 \quad \forall n,t,w \tag{A21}$$

$$0\le\left(\delta_{ntw}^{DA}+\pi\right)\perp\theta_{ntw}^{D,\min}\ge 0 \quad \forall n,t,w \tag{A22}$$

Appendix B

The objective function (1) and the constraints (2)-(12) and (A1)-(A22) form a nonlinear single-level MPEC model. There are two nonlinear terms in the problem, which are provided and linearized as follows.

1) In the objective function (1), the bilinear term $\sum_{i=1}^{I}\sum_{p=1}^{P}\lambda_{(n:i\in\psi_n^I)tw}^{DA}P_{pitw}^{WD}+\sum_{v=1}^{V}\lambda_{(n:v\in\psi_n^V)tw}^{DA}\left(P_{vtw}^{VI}-P_{vtw}^{VD}\right)$ can be linearized using the strong duality theorem, (A1)-(A3), (A10), (A12), (A14), (A16), and (A18).

First, according to the strong duality theorem, the primal optimal objective of the proposed lower-level problem should be equal to its dual optimal objective. Thus, (B1) can be derived.

$$\begin{aligned}&\sum_{i=1}^{I}\sum_{p=1}^{P}\lambda_{pit}^{WD}P_{pitw}^{WD}+\sum_{v=1}^{V}\lambda_{vt}^{VI}P_{vtw}^{VI}+\sum_{j=1}^{J}\sum_{b=1}^{B}\lambda_{bjt}^{CD}P_{bjtw}^{CD}-\sum_{v=1}^{V}\lambda_{vt}^{VD}P_{vtw}^{VD}-\\&\sum_{l=1}^{D}\sum_{e=1}^{E}\lambda_{elt}^{LD}P_{eltw}^{LD}=-\sum_{i=1}^{I}\sum_{p=1}^{P}\mu_{pitw}^{W,\max}P_{pit}^{WD,\max}-\sum_{j=1}^{J}\sum_{b=1}^{B}\mu_{bjtw}^{CD,\max}P_{bjt}^{CD,\max}-\\&\sum_{v=1}^{V}\mu_{vtw}^{VI,\max}P_{vt}^{VI,\max}-\sum_{v=1}^{V}\mu_{vtw}^{VD,\max}P_{vt}^{VD,\max}-\sum_{l=1}^{D}\sum_{e=1}^{E}\mu_{eltw}^{LD,\max}P_{elt}^{LD,\max}-\\&\sum_{k=1}^{K}C_k^{\max}\left(\Phi_{ktw}^{D,\max}+\Phi_{ktw}^{D,\min}\right)-\sum_{n=1}^{N}\pi\left(\theta_{ntw}^{D,\max}+\theta_{ntw}^{D,\min}\right)\end{aligned} \tag{B1}$$

where the terms on the left- and right-hand sides of the equal sign are the prime and dual objectives of the lower-level problem, respectively.

Next, according to (A10), (A12), (A14), (A16), and (A18), the following equations (B2)-(B6) are obtained, respectively.

$$P_{pitw}^{WD}\mu_{pitw}^{WD,\min}=0 \quad \forall p,\forall i,\forall t,\forall w \tag{B2}$$

$$P_{vtw}^{VI}\mu_{vtw}^{VI,\min}=0 \quad \forall v,\forall t,\forall w \tag{B3}$$

$$P_{vtw}^{VD}\mu_{vtw}^{VD,\min}=0 \quad \forall v,\forall t,\forall w \tag{B4}$$

$$P_{bjtw}^{CD}\mu_{bjtw}^{CD,\min}=0 \quad \forall b,\forall j,\forall t,\forall w \tag{B5}$$

$$P_{eltw}^{LD}\mu_{eltw}^{LD,\min}=0 \quad \forall e,\forall l,\forall t,\forall w \tag{B6}$$

Then, according to (A1)-(A3) and (B2)-(B6), (B7) can be obtained.

$$\begin{aligned}&\sum_{i=1}^{I}\sum_{p=1}^{P}\lambda_{\left(n:i\in\psi_n^I\right)tw}^{DA}P_{pitw}^{WD}+\sum_{v=1}^{V}\lambda_{\left(n:v\in\psi_n^V\right)tw}^{DA}\left(P_{vtw}^{VI}-P_{vtw}^{VD}\right)=\\&\sum_{i=1}^{I}\sum_{p=1}^{P}\left(\mu_{pitw}^{WD,\max}-\mu_{pitw}^{WD,\min}+\lambda_{pit}^{WD}\right)P_{pitw}^{WD}+\\&\sum_{v=1}^{V}\left(\mu_{vtw}^{VI,\max}-\mu_{vtw}^{VI,\min}+\lambda_{vt}^{VI}\right)P_{vtw}^{VI}+\\&\sum_{v=1}^{V}\left(\mu_{vtw}^{VD,\min}-\mu_{vtw}^{VD,\max}+\lambda_{vt}^{VD}\right)P_{vtw}^{VD}=\sum_{i=1}^{I}\sum_{p=1}^{P}\left(\mu_{pitw}^{WD,\max}+\lambda_{pit}^{WD}\right)P_{pitw}^{WD}+\\&\sum_{v=1}^{V}\left(\mu_{vtw}^{VI,\max}+\lambda_{vt}^{VI}\right)P_{vtw}^{VI}+\sum_{v=1}^{V}\left(-\mu_{vtw}^{VD,\max}+\lambda_{vt}^{VD}\right)P_{vtw}^{VD}\end{aligned} \tag{B7}$$

Finally, (B8) can be derived by using (B7) and (B1).

$$\begin{aligned}&\sum_{i=1}^{I}\sum_{p=1}^{P}\left(\mu_{pitw}^{WD,\max}+\lambda_{pit}^{WD}\right)P_{pitw}^{WD}+\sum_{v=1}^{V}\left(\mu_{vtw}^{VI,\max}+\lambda_{vt}^{VI}\right)P_{vtw}^{VI}+\\&\sum_{v=1}^{V}\left(-\mu_{vtw}^{VD,\max}+\lambda_{vt}^{VD}\right)P_{vtw}^{VD}=-\sum_{j=1}^{J}\sum_{b=1}^{B}\mu_{bjtw}^{CD,\max}P_{bjt}^{CD,\max}-\\&\sum_{j=1}^{J}\sum_{b=1}^{B}\lambda_{bjt}^{CD}P_{bjtw}^{CD}+\sum_{l=1}^{D}\sum_{e=1}^{E}\lambda_{elt}^{LD}P_{eltw}^{LD}-\sum_{l=1}^{D}\sum_{e=1}^{E}\mu_{eltw}^{LD,\max}P_{elt}^{LD,\max}-\\&\sum_{k=1}^{K}C_k^{\max}\left(\Phi_{ktw}^{D,\max}+\Phi_{ktw}^{D,\min}\right)-\sum_{n=1}^{N}\pi\left(\theta_{ntw}^{D,\max}+\theta_{ntw}^{D,\min}\right)\end{aligned} \tag{B8}$$

where the terms on the right-hand side of the equal sign is obtained by linearizing the nonlinear terms $\sum_{i=1}^{I}\sum_{p=1}^{P}\lambda_{\left(n:i\in\psi_n^I\right)tw}^{DA}P_{pitw}^{WD}+\sum_{v=1}^{V}\lambda_{\left(n:v\in\psi_n^V\right)tw}^{DA}\left(P_{vtw}^{VI}-P_{vtw}^{VD}\right)$ in (1).

2) The MPEC model includes nonlinear complementarity constraints (A9)-(A22). According to [30], the complementarity constraint in the form of $0\le P\perp Q\ge 0$ can be substituted by the following formulation:

$$P\ge 0, Q\ge 0; P\le \mu M; Q\le\left(1-\mu\right)M; \mu\in\{0,1\} \tag{B9}$$

As a result, the nonlinear constraints (A9)-(A22) are linearized and the MPEC model is converted into an MILP model.

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