Optimal Bidding Strategy of a Strategic Wind Power Producer in the Short-Term Market

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***Abstract*—Wind energy is a clean and renewable energy source which is rapidly growing globally. As the penetration level of wind power grows, the system operators need to consider wind power producers as strategic producers whose bidding behaviors will have an impact on the locational marginal prices. This paper proposes a bilevel stochastic optimization model to obtain the optimal bidding strategy for a strategic wind power producer in the short-term electricity market. The upper level problem of the model maximizes the profit of the wind power producer, while the lower level problem represents the market clearing processes of both day-ahead and real-time markets. The uncertainties in the demand, the wind power production, and the bidding strategies of the strategic conventional power producers are represented by scenarios in the model. The conditional value at risk of the selected worst scenarios is included in the objective function for managing the risk due to uncertainties. Using the duality theory and Karush–Kuhn–Tucker condition, the bilevel model is transferred into a mixed-integer linear problem. Case studies are performed to show the effectiveness of the proposed model.**

***Index Terms*—Bidding strategy, electricity market, mathematical program with equilibrium constraints (MPEC), stochastic optimization, wind power producer.**

NOMENCLATURE

Indices and Sets:

t	Index for time periods, running from 1 to T.
i	Index for the conventional power producers, running from 1 to I.
j	Index for the wind power generating units owned by the strategic producer, running from 1 to J.
d	Index for demands, running from 1 to D.
ω, ω'	Index of scenarios, running from 1 to Ω.
b	Index of energy blocks offered by a power producer, running from 1 to B.
l	Index of demand blocks, running from 1 to L.
m, n	Indices of system buses, running from 1 to M/N.
Ψ_m^I	Set of indices of the conventional power producers located at bus m.
Ψ_m^D	Set of indices of the demands located at bus m.
Ψ_m^W	Set of indices of the wind power units located at bus m.
ϕ_m	Set of indices of the buses connected to bus m.

Decision Variables:

λ_{bjt}^{WD}	Offer price of block b of the wind generating unit j in a period t in the day-ahead market.
λ_{jt}^{WR}	Offer price of the wind generating unit j in a period t in the real-time market.
p_{bjt}^{WD}	Produced power of block b of the wind generating unit j in a period t in the day-ahead market.
$P_{jt\omega}^{WR}$	Rescheduled power of the wind generating unit j in a period t in the real-time market.
p_{bit}^{CD}	Power of block b produced by the conventional power producer i in a period t in the day-ahead market.
$P_{it}^{CR+}/P_{it}^{CR-}$	Increased/decreased power of the conventional power producer i in a period t in the real-time market.
p_{ldt}^{LD}	Power bought of block l of the demand d in a period t in the day-ahead market.
P_{dt}^{LR}	Accepted deviation of the demand d in a period t in the real-time market.
$\lambda_{mt}^{\mathrm{DA}}/\lambda_{mt}^{\mathrm{RT}}$	Day-ahead/real-time locational marginal price (LMP) at bus m in a period t.
R_{it}^U/R_{it}^D	Up/down reserve scheduled for the conventional power producer i in a period t.
R_t^U/R_t^D	Total up/down reserve scheduled in a period t.
r_{it}^U/r_{it}^D	Up/down reserve deployed for the conventional power producer i in a period t.
$\delta_{mt}^D/\delta_{mt}^R$	Voltage angle of bus m in a period t in the day-ahead/real-time market.
ζ	Auxiliary variable used to compute CVaR.
η_ω	Auxiliary variable used to compute CVaR in a scenario.

Random Variables:

λ_{bit}^{CD}	Offer price of block b of the conventional power producer i in a period t in the day-ahead market

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P_{jt}^{Wf} Forecasted production of the wind generating unit j in a period t.

P_{dt}^{LRf} Forecasted deviation of demand d in a period t in the real-time market.

Other Variables:

$\mathrm{CV}aR_{\alpha}$ Conditional value at risk at α confidential interval.

$p_{\mathrm{bit}}^{\mathrm{CD}\max}$ Capacity of block b of the conventional power producer i in a period t in the day-ahead market.

λ_{ldt}^{LD} Bidding price of block l of the demand d in a period t in the day-ahead market.

$p_{ldt}^{LD\max}$ Capacity of block l of the demand d in a period t in the day-ahead market.

$\lambda_{it}^{RU}/\lambda_{it}^{RD}$ Offer price of the up/down reserve of the conventional power producer i in a period t.

$\lambda_{it}^{CR+}/\lambda_{it}^{CR-}$ Offer price of the increased/decreased power of the conventional power producer i in a period t in the real-time market.

λ_{dt}^{LR} Bidding price of the deviated demand d in a period t in the real-time market.

σ_{t}^{D} Standard deviation of the total forecasted demand in a period t.

σ_{jt}^{W} Standard deviation of the forecasted power of the wind generating unit j in a period t.

The variables, if augmented with a subscript ω, represent their realization in a scenario ω.

Constants and Parameters:

$P_{i}^{\max}$ Maximum output of the conventional power producer i.

$P_{j}^{W\max}$ Installed capacity of wind power generating unit j.

π_{ω} Probability of occurrence of a scenario ω.

B_{mn} Imaginary part of the admittance of line $m-n$.

$C_{mn}^{\max}$ Transmission capacity of line $m-n$.

$\delta_{m}^{\max}$ Upper limit of voltage magnitude of bus m.

$\delta_{m}^{\min}$ Lower limit of voltage magnitude of bus m.

$P_{i}^{\max+}/P_{i}^{\max-}$ Maximum increased/decreased power that can be provided by the conventional power producer i.

$R_{i}^{U\max}/R_{i}^{D\max}$ Maximum up/down reserve that can be provided by the conventional power producer i.

κ Factor relating the system reserve requirement to the standard deviations of load and wind power.

$\lambda^{\mathrm{Cap}D}$ Cap bidding price in the day-ahead market.

$\lambda^{\mathrm{Cap}R}$ Cap bidding price in the real-time market.

α Per-unit confidence level.

β Risk-aversion parameter.

I. Introduction

THE installed capacity of wind power is increasing rapidly all around the world. The global installed wind capacity reached 282 GW at the end of 2012 [1]. The United States, Germany, Spain, and China are the leading countries in terms of installed wind capacity. According to a recent report [1], the total installed wind capacity in the United States reached over 59 GW with nearly 13 GW of newly installed wind capacity in 2012. Due to the uncertainty and intermittency of wind power, the increasing penetration of wind power into the electric power system will pose challenges to power system operators.

In the United States, around 69% of the installed wind power was sold through power purchasing agreements (PPAs) at a fixed price in 2012 [2]. However, since the PPA price continuously declines after reaching the peak in 2008 and the availability of PPA contracts has been limited since 2010, wind power producers can no longer obtain stable revenues through PPAs. As a consequence, wind power producers are becoming more interested in selling power into the electricity market. Currently, some of the U.S. market operators, e.g., the Midwest Independent System Operator (MISO), Electric Reliability Council of Texas (ERCOT), Pennsylvania-New Jersey-Maryland Interconnection (PJM), and New York ISO, allow wind power producers to submit their day-ahead commitments into the markets. Same as the conventional power producers, the wind power producers are subjected to monetary penalties if their real-time productions deviate from their commitments.

Due to the unpredictable characteristics of wind, wind power producers are exposed to high risks in a competitive electricity market. Some work has presented using stochastic models to generate optimal bidding strategies for wind power producers to hedge against production uncertainty in the day-ahead or adjustment market [3]–[5]. The stochastic models were proven outperforming the deterministic ones generated by using forecasted values directly [6]. Another risk mitigation approach is based on a combined and coordinated use of wind power and energy storage or thermal units [7]–[10].

Most existing models in the literature generating bidding strategies for wind power producers in the short-term market are based on an assumption that wind power producers are price-takers whose bidding strategies would not influence the market price. In this case, the wind power producers would only need to forecast the market price and use it as a stochastic variable to determine their bidding strategies. However, as the so-called Lerner index [11] has stated that the extent to which the bidding prices exceed the marginal cost is a measurement of market power, a wind power producer whose marginal cost is lower than that of thermal power producers has nonnegligible market power and should be considered as a price-maker.

The strategic bidding model for a price-maker producer in an electricity market can be formulated as a bilevel optimization problem. The profit is maximized (or the cost is minimized) for the producer at the upper level problem with the information (e.g., cleared power production, scheduled amount of reserve, and LMPs) obtained from the lower level problem, which represents the market clearing process conducted by the market operator. The low-level problems can be replaced by its first-order optimality conditions, such as the widely used Karush–Kuhn–Tucker (KKT) condition [12]. Thus, the original bilevel optimization problem is transformed to a single-level problem, which is a mathematical program with equilibrium constraints (MPEC) [13]. The MPEC approach has been widely used to obtain the optimal bidding strategies for conventional power producers [14]–[16].

Stochastic programming [17] provided a suitable tool to model the uncertainties faced by wind power producers in the short-term market. For example, the uncertainties in wind power production and real-time demand can be modeled as random variables. In [18] and [19], the stochastic programming approach has been combined with the MPEC approach to solve the long-term wind power investment problem. The medium-term decision-making problem of a retailer in the future market and the pool could also be modeled using the stochastic MPEC approach [20]. Reference [21] analyzed the equilibrium of an oligopolistic market where each strategic producer may own wind facilities. However, little work has been reported on generating optimal bidding strategy for a wind power producer using a stochastic MPEC approach. The most recent work [22] and [23] proposed models to generate the strategic bidding strategy for a wind power producer. In [22], the wind power producer only behaved strategically in the real-time market, while [23] only considered the wind power producer to behave strategically in the day-ahead market. Neither [22] nor [23] considered risk management that is important for optimization involving uncertainties. Furthermore, neither [22] nor [23] considered the uncertainty of the bidding strategies of other strategic conventional power producers in the market.

This paper proposes a stochastic MPEC model for generating the optimal bidding strategies for price-maker wind power producers. Compared with [22] and [23], the main contributions of this paper are as follows.

1) The wind power producer is considered to be a strategic player in both day-ahead and real-time markets. A comparison with the cases in which the wind power producer only behaves strategically in either the day-ahead or the real-time market is studied.
2) The uncertainties of the bidding strategies of other strategic power producers are considered in the model.
3) Risk management is considered in the model.
4) The proposed model can be stepwise bidding curves for the wind power producer.

The paper is organized as follows. Section II presents the market framework and modeling of uncertainties. Section III provides the detailed mathematical formulation of the bilevel stochastic optimization model. Section IV transfers the bilevel model to a single-stage stochastic MPEC model and further to a mixed-integer linear programming (MILP) model. Section V provides case studies of using the proposed model to generate the optimal bidding strategy for a strategic wind power producer. Section VI concludes the paper.

II. Model Description

A. Market Framework

In a pool-based electricity market, suppliers including wind power producers are allowed to submit energy offer curves into the day-ahead energy and reserve markets for each hour of the next operating day. Once the day-ahead market is closed, the ISOs or RTOs in most U.S. market aggregate the offer curves and determine the hourly LMPs, the reserve market clearing price, and the cleared energy volume of each producer. For each hour, producers are paid for the cleared energy volume at the day-ahead LMP. Afterward, the real-time market is performed just minutes before the actual power delivery of each producer, where supply resources are selected to increase or decrease their generation to maintain the real-time balance of the system. After the real-time market is cleared, the real-time LMPs, the deployment of reserve, and the increased or decreased energy volume of each generator will be decided. In most U.S. market, the deviations of the actual generation and load from what were scheduled in the day-ahead market are settled at the real-time energy price in the real-time market. Those market participants providing extra supply (or having less than the scheduled load) will be paid at the real-time energy price, while those providing less than the scheduled supply (or having extra demand) will pay at the real-time energy price.

B. Uncertainty Modeling in Market Clearing Process

The uncertainties of the model in this paper come from three main sources: 1) system load; 2) wind power production; and 3) bidding strategies of strategic power producers. Appropriately modeling these uncertainties is crucial for a wind power producer to obtain the optimal bidding strategy.

The main uncertainty in the day-ahead market clearing process comes from the load and wind forecast errors and the bidding strategies of other strategic power producers. The load and wind forecast errors are unintentional and depend on the forecasting models. In this paper, these forecast errors are handled by up and down reserves, which are scheduled as functions of the standard deviations of the forecasted wind power and the total forecasted demand of the system as follows [24]:

$$R_t^U = R_t^D = \kappa\sqrt{\left(\sigma_t^D\right)^2 + \sum\nolimits_j \left(\sigma_{jt}^W\right)^2} \tag{1}$$

where κ is a parameter decided by the system operator and is selected to be 3 in this paper.

The reserve clearing process is assumed to be independent from the day-ahead energy clearing and is modeled as

$$\min_{R_{it}^U, R_{it}^D} \sum\nolimits_i \lambda_{it}^{RU} R_{it}^U + \lambda_{it}^{RD} R_{it}^D \tag{2a}$$

Subject to

$$0 \le R_{it}^U \le R_i^{U\max} \quad \forall i, t \tag{2b}$$

$$0 \le R_{it}^D \le R_i^{D\max} \quad \forall i, t \tag{2c}$$

$$\sum\nolimits_i R_{it}^U = R_t^U \quad \forall t \tag{2d}$$

$$\sum\nolimits_i R_{it}^D = R_t^D \quad \forall t. \tag{2e}$$

The objective function (2a) is to minimize the total cost of reserve. Constraints (2b) and (2c) are the reserve bounds for each conventional generating unit. The reserve requirement is met in constraints (2d) and (2e).

The uncertain bidding prices of other strategic conventional power producers who also have the market power to change the market clearing price are forecasted and included as independent random variables in the day-ahead market clearing model. In this paper, these random variables are represented via scenarios. The number of the scenarios will increase rapidly with the number of the strategic power producers whose uncertain bidding prices are considered. In fact, if the uncertainty (i.e., change) of the bidding price of another strategic producer has no or negligible impact on the LMPs at the buses having generating units of the wind power producer, it is not necessary for the wind power producer to consider the uncertainty of the bidding price of that strategic producer. In this paper, the sensitivities of the LMPs at the buses having the wind power producer's generating units to the bidding prices of other strategic conventional power producers are analyzed using the perturbation approach proposed in [25]. The details of this method are provided in the Appendix. Using this method, the strategic conventional power producers that have nonnegligible LMP sensitivities to the wind power producer will be identified and the uncertainties of their bidding prices will be considered in the proposed model. Suppose that I^S ($I^S \leq I$) strategic conventional power producers are selected and each of them has Ω_{i^S} ($i^S = 1, \ldots, I^S$) bidding prices. Then, the total number of scenarios in the day-ahead market will be $\Omega^D = \Pi_{i^S=1}^{I^S} \Omega_{i^S}$.

In the real-time market clearing process, the main uncertainties come from the intentional misscheduling of load and wind power production deviation. If the power purchasers predict that the real-time price will be lower than the day-ahead price, they may intentionally underschedule load in the day-ahead market and buy extra demand in the real-time market at the real-time price. Otherwise, if the power purchasers expect that the real-time price will be higher than day-ahead price, they may intentionally over-schedule load and sell any extra energy procured in the day-ahead market back to the system at the real-time price. The behavior of these purchasers will increase the real-time price volatility. For a wind power producer, the deviation of the actual production from that scheduled in the day-ahead market will be balanced in the real-time market. If the actual production is less than the day-ahead scheduled, the wind producer will have to buy the deviated power at the real-time price. Otherwise, the wind producer can bid the extra power into the real-time market and get paid for the accepted power at the real-time price.

The uncertainties in the day-ahead and real-time markets are considered as random variables and can be represented via scenarios. The method to generate a large number of scenarios for random variables and then reduce them to a sufficiently small number of scenarios has been explained in [26]. That method will be applied in this paper for scenario generation and reduction of the forecasted bidding prices of other selected strategic conventional power producers, real-time demand, and wind power production. The correlation between real-time demand and wind power production is considered

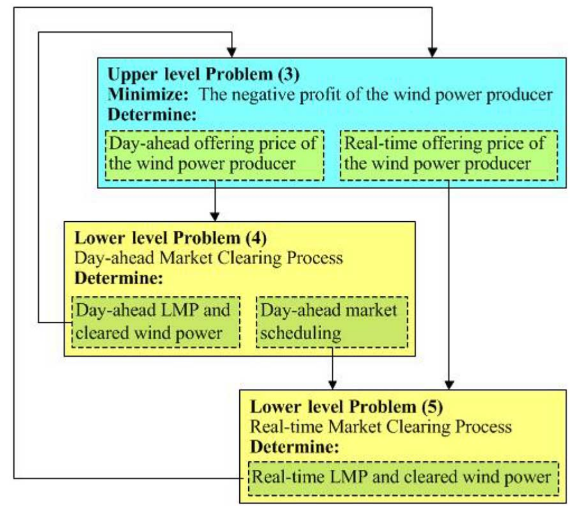

Fig. 1. Structure of the proposed bilevel stochastic optimization model.

in the scenario generating process and then the fast-forward scenario reduction technique [26] is applied to reduce the scenarios to a sufficiently low number. If Ω^L reduced scenarios are selected for the real-time demand and Ω_j^W reduced scenarios are selected for the power production of each wind generating unit j, the total number of scenarios in the real-time market will be $\Omega = \Omega^D \Omega^L \prod_j \Omega_j^W$. Then, the real-time market will be cleared and the resulting real-time LMPs will be obtained for each scenario. In order to connect the forecasted wind power production with the wind power bid in the day-ahead market, Ω_j^W is set equal to B, which is the maximum number of energy blocks. The generated scenarios of the forecasted production of each wind generating unit j in a period t will be sorted in an increasing manner to form a scenario set $WP(j,\, t) = \{P_{jt\omega}^{Wf}$, $\omega = 1, 2, \ldots, \Omega_j^W\}$.

The decision process of the wind power producer can be arranged in a two-stage scenario tree. In the first stage, the producer determines the bidding strategy for the day-ahead market for each period of the market horizon. The second-stage decisions are made for each realized scenario, where the real-time demand and wind power production become known.

III. Bilevel Stochastic Optimization Model for a Strategic Wind Power Producer

A. Bilevel Model Structure

The problem to determine the optimal bidding strategy for a strategic wind power producer is formulated as a bilevel stochastic optimization model. Fig. 1 shows the structure of the bilevel model, which consists of an upper–lower problem and two lower level problems. The upper level problem maximizes the total profit obtained by the wind power producer in both day-ahead and real-time markets to determine its optimal bidding curves in both markets. The maximal profit and the resulting bidding curves depend on the cleared information (LMPs and scheduled energy) in the day-ahead and real-time markets, which will be obtained in the lower level problems. One lower level problem collects the bidding information of each producer and runs the day-ahead market clearing process to generate the day-ahead LMPs and energy schedule for each producer. The other lower level problem is carried out after the day-ahead clearing to deal with the real-time energy deviation. This real-time market clearing process depends on not only the real-time offering curve of each producer but also the day-ahead energy schedule. Both the real-time LMPs and the real-time energy schedule will be announced after the clearing.

B. Upper Level Problem

The upper level problem (3) maximizing the total profit of the wind power producer in the day-ahead and real-time market is shown as follows:

$$\min_{\Xi} \sum\nolimits_{jt\omega} \pi_\omega \Big[\sum\nolimits_b \Big(-\lambda^{DA}_{(m:j\in\Psi^W_m)t\omega} p^{WD}_{bjt\omega}\Big) - \lambda^{RT}_{(m:j\in\Psi^W_m)t\omega} P^{WR}_{jt\omega}\Big] - \beta\left(\zeta - \frac{1}{1-\alpha}\sum\nolimits_\omega \pi_\omega \eta_\omega\right) \quad \text{(3a)}$$

Subject to

$$0 \le \lambda^{WD}_{(b-1)jt\omega} \le \lambda^{WD}_{bjt\omega} \le \lambda^{\mathrm{Cap}D} \quad \forall j, b \ge 2, t, \omega \quad \text{(3b)}$$

$$0 \le \lambda^{WR}_{jt\omega} \le \lambda^{\mathrm{Cap}R} \quad \forall j, t, \omega \quad \text{(3c)}$$

$$\eta_\omega \ge 0 \quad \forall \omega \quad \text{(3d)}$$

$$\zeta - \eta_\omega \le \sum\nolimits_{jt}\Big[\sum\nolimits_b \Big(-\lambda^{DA}_{(m:j\in\Psi^W_m)t\omega} p^{WD}_{bjt\omega}\Big) + \lambda^{RT}_{(m:j\in\Psi^W_m)t\omega} P^{WR}_{jt\omega}\Big] \quad \forall\omega \quad \text{(3e)}$$

$$(4) \quad \text{(3f)}$$

$$(5) \quad \text{(3g)}$$

where $m{:}w \in \Psi^W_m$ denotes the bus where the wind power generating unit w is located, and $\Xi = \{\lambda^{WD}_{bjt\omega}, \lambda^{WR}_{jt\omega}, \varsigma, \eta_\omega, \Xi^{\mathrm{D}}, \Xi^R\}$ are the set of all decision variables of the problem (3), where Ξ^{D} and Ξ^R are the sets of all the decision variables in the lower level problems (4) and (5), respectively, and will be defined later.

The objective function (3a) minimizes the sum of two terms: 1) the negative expected profit of the wind power producer, which is the negative revenue obtained in the day-ahead market plus the negative revenue from the real-time market and 2) the negative CVaR_α multiplied by the weighting factor β. In (3a), $\lambda^{DA}_{(m:j\in\Psi^W_m)t\omega}$and $p^{WD}_{bjt\omega}$ are the variables determined in the lower level problem (4), while $\lambda^{RT}_{(m:j\in\Psi^W_m)t\omega}$ and $P^{WR}_{jt\omega}$ are the variables determined in the lower level problem (5). Constraints (3b) and (3c) enforce the acceptable day-ahead and real-time bidding prices and nondecreasing day-ahead bidding curves of the wind power producer. Constraints (3d) and (3e) are used to compute the CVaR [28], which is used in this paper as a measurement for risk. The CVaR_α represents the expected profit associated with the $(1-\alpha)\times 100\%$ worst scenarios. The weighting parameter β is set by the wind power producer to model the tradeoff between profit and risk. If the wind power producer is willing to gain less profit in order to bear less risk, it will select a higher value for β.

C. Lower Level Problem for Day-Ahead Market Clearing

The lower level problem (4) is formulated to represent the day-ahead market clearing process as follows:

$$\min_{\Xi^D} \sum\nolimits_{bi} \lambda^{CD}_{bit\omega} p^{CD}_{bit\omega} + \sum\nolimits_{bj} \lambda^{WD}_{bjt\omega} p^{WD}_{bwt\omega} - \sum\nolimits_{ld} \lambda^{LD}_{ldt} p^{LD}_{ldt\omega} \quad \text{(4a)}$$

Subject to

$$\sum\nolimits_{l(d\in\Psi^D_m)} p^{LD}_{ldt\omega} - \sum\nolimits_{b(i\in\Psi^I_m)} p^{CD}_{bit\omega} - \sum\nolimits_{b(j\in\Psi^W_m)} p^{WD}_{bjt\omega} + \sum\nolimits_{n\in\Phi_m} B_{mn}\left(\delta^D_{mt\omega} - \delta^D_{nt\omega}\right) = 0{:}\lambda^{DA}_{mt\omega} \quad \forall m, t, \omega \quad \text{(4b)}$$

$$0 \le p^{CD}_{bit\omega} \le p^{CD\max}_{bit}{:}\mu^{C\max}_{bit\omega}, \mu^{C\min}_{bit\omega} \quad \forall b, i, t, \omega \quad \text{(4c)}$$

$$0 \le p^{WD}_{bjt\omega} \le P^{Wf}_{jtb}{:}\mu^{W\max}_{bjt\omega}, \mu^{W\min}_{bjt\omega}, b = 1 \quad \forall j, t, \omega \quad \text{(4d)}$$

$$0 \le p^{WD}_{bjt\omega} \le P^{Wf}_{jtb} - P^{Wf}_{jt(b-1)}{:}\mu^{W\max}_{bjt\omega}, \mu^{W\min}_{bjt\omega} \quad \forall b \ge 2, j, t, \omega \quad \text{(4e)}$$

$$0 \le p^{LD}_{ldt\omega} \le p^{LD\max}_{ldt}{:}\mu^{L\max}_{ldt\omega}, \mu^{L\min}_{ldt\omega} \quad \forall l, d, t, \omega \quad \text{(4f)}$$

$$|B_{mn}\left(\delta^D_{mt\omega} - \delta^D_{nt\omega}\right)| \le C^{\max}_{mn}{:}\beta^{D\max}_{mnt\omega}, \beta^{D\min}_{mnt\omega} \quad \forall m, n \in \Phi_m, t, \omega \quad \text{(4g)}$$

$$\delta^{\min}_m \le \delta^D_{mt\omega} \le \delta^{\max}_m{:}\theta^{D\max}_{mt\omega}, \theta^{D\min}_{mt\omega} \quad \forall m, t, \omega \quad \text{(4h)}$$

$$\delta^D_{mt\omega} = 0{:}\theta^{D1}_{t\omega}, m = 1 \quad \forall t, \omega \quad \text{(4i)}$$

where P^{Wf}_{jtb} is the bth element in the set $WP(j,\ t)$, and $\Xi^{\mathrm{D}} = \{p^{CD}_{bit\omega},\ p^{WD}_{bjt\omega},\ p^{LD}_{ldt\omega},\ \delta^D_{mt\omega},\ \lambda^{DA}_{mt\omega},\ \mu^{C\max}_{bit\omega},\ \mu^{C\min}_{bit\omega},\ \mu^{W\max}_{bjt\omega},\ \mu^{W\min}_{bjt\omega},\ \mu^{L\max}_{ldt\omega},\ \mu^{L\min}_{ldt\omega},\ \beta^{D\max}_{mnt\omega},\ \beta^{D\min}_{mnt\omega},\ \theta^{D\max}_{mt\omega},\ \theta^{D\min}_{mt\omega},\ \theta^{D1}_{t\omega}\}$ is the set of all decision variables of the problem (4). The decision variable set contains both primal and dual variables, where the dual variables are defined following the colon in each constraint.

The objective function (4a) minimizes the total cost of energy offered by both conventional and wind power producers minus the revenue from supplying demand in each period and each scenario. Equation (4b) enforces the day-ahead power balance at each bus. Constraints (4c)–(4e) represent the limits of the power offered by the conventional and wind power units in each block. Constraint (4f) represents the bounds of the demand in each block. Constraint (4g) imposes the transmission capacity limits of each power line. The voltage angle limits of each bus are expressed in constraint (4h). The reference bus is selected in (4i). Note that if the uncertainty of the bidding prices of the conventional power producer i is not considered, then $\lambda^{CD}_{bit\omega} = \lambda^{CD}_{bit\omega} \quad \forall\omega, \omega'$.

D. Lower Level Problem for Real-Time Market Clearing

The lower level problem (5) modeling the real-time market clearing process is formulated as follows:

$$\min_{\Xi^R} \sum\nolimits_i \left(\lambda^{CR+}_{it} P^{CR+}_{it\omega} - \lambda^{CR-}_{it} P^{CR-}_{it\omega}\right) + \sum\nolimits_j \lambda^{WR}_{jt\omega} P^{WR}_{jt\omega} + \sum\nolimits_i \left(\lambda^{RU}_{it} r^U_{it\omega} + \lambda^{RU}_{it} r^U_{it\omega}\right) - \sum\nolimits_d \lambda^{LR}_{dt\omega} P^{LR}_{dt\omega} \quad \text{(5a)}$$

Subject to

$$\sum_{d\in\Psi_m^D}\left(P_{dt\omega}^{LR}+\sum_l p_{ldt\omega}^{LD}\right)-\sum_{b(i\in\Psi_m^I)}p_{bit\omega}^{CD}$$
$$-\sum_{i\in\Psi_m^I}\left(P_{it\omega}^{CR+}-P_{it\omega}^{CR-}+r_{it\omega}^{U}-r_{it\omega}^{D}\right)$$
$$-\sum_{b(j\in\Psi_m^W)}p_{bjt\omega}^{WD}-\sum_{j\in\Psi_m^W}P_{jt\omega}^{WR}$$
$$+\sum_{n\in\Phi_m}B_{mn}\left(\delta_{mt\omega}^{R}-\delta_{nt\omega}^{R}\right)=0{:}\lambda_{mt\omega}^{RT}\quad\forall m,t,\omega \tag{5b}$$

$$0\le P_{it\omega}^{CR+}\le P_i^{\max+}{:}\mu_{it\omega}^{\max+},\mu_{it\omega}^{\min+}\quad\forall i,t,\omega \tag{5c}$$

$$0\le P_{it\omega}^{CR-}\le P_i^{\max-}{:}\mu_{it\omega}^{\max-},\mu_{it\omega}^{\min-}\quad\forall i,t,\omega \tag{5d}$$

$$P_{it\omega}^{CR+}\le P_i^{\max}-\sum_b p_{bit}^{CD}{:}\mu_{it\omega}^{CR+}\quad\forall i,t,\omega \tag{5e}$$

$$P_{it\omega}^{CR-}\le\sum_b p_{bit}^{CD}{:}\mu_{it\omega}^{CR-}\quad\forall i,t,\omega \tag{5f}$$

$$-\sum_b p_{bjt}^{WD}\le P_{jt\omega}^{WR}\le P_{jt\omega}^{Wf}$$
$$-\sum_b p_{bjt}^{WD}{:}\mu_{jt\omega}^{WR\max},\mu_{jt\omega}^{WR\min}\quad\forall j,t,\omega \tag{5g}$$

$$\begin{cases}0\le P_{dt\omega}^{LR}\le P_{dt\omega}^{LRf},{:}\mu_{dt\omega}^{LR\max},\mu_{dt\omega}^{LR\min} & \forall d,t,\omega,\text{if}P_{dt\omega}^{LRf}\ge0\\ P_{dt\omega}^{LRf}\le P_{dt\omega}^{LR}\le0,{:}\mu_{dt\omega}^{LR\max},\mu_{dt\omega}^{LR\min} & \forall d,t,\omega,\text{if}P_{dt\omega}^{LRf}<0\end{cases} \tag{5h}$$

$$0\le r_{it\omega}^{U}\le R_{it}^{U}{:}\varphi_{it\omega}^{U\max},\varphi_{it\omega}^{U\min}\quad\forall i,t,\omega \tag{5i}$$

$$0\le r_{it\omega}^{D}\le R_{it}^{D}{:}\varphi_{it\omega}^{D\max},\varphi_{it\omega}^{D\min}\quad\forall i,t,\omega \tag{5j}$$

$$|B_{mn}\left(\delta_{mt\omega}^{R}-\delta_{nt\omega}^{R}\right)|$$
$$\le C_{mn}^{\max}{:}\beta_{mnt\omega}^{R\max},\beta_{mnt\omega}^{R\min}\quad\forall m,n\in\Phi_m,t,\omega \tag{5k}$$

$$\delta_m^{\min}\le\delta_{mt\omega}^{R}\le\delta_{mt}^{\max}{:}\theta_{mt\omega}^{R\max},\theta_{mt\omega}^{R\min}\quad\forall m,t,\omega \tag{5l}$$

$$\delta_{mt\omega}^{R}=0{:}\theta_{t\omega}^{R1},m=1\quad\forall t,\omega \tag{5m}$$

where Ξ^R is the set of all primal and dual decision variables in the problem (5), i.e., $\Xi^R=\{P_{it\omega}^{CR+}, P_{it\omega}^{CR-}, P_{jt\omega}^{WR}, P_{dt\omega}^{LR}, r_{it\omega}^{U}, r_{it\omega}^{D}, \delta_{mt\omega}^{R}, \lambda_{mt\omega}^{RT}, \mu_{it\omega}^{\max+}, \mu_{it\omega}^{\min+}, \mu_{it\omega}^{\max-}, \mu_{it\omega}^{\min-}, \mu_{it\omega}^{CR+}, \mu_{it\omega}^{CR-}, \mu_{jt\omega}^{WR\max}, \mu_{jt\omega}^{WR\min}, \mu_{dt\omega}^{LR\max}, \mu_{dt\omega}^{LR\min}, \varphi_{it\omega}^{U\max}, \varphi_{it\omega}^{U\min}, \varphi_{it\omega}^{Dmax}, \varphi_{it\omega}^{D\min}, \beta_{mnt\omega}^{R\max}, \beta_{mnt\omega}^{R\min}, \theta_{mt\omega}^{R\max}, \theta_{mt\omega}^{R\min}, \theta_{t\omega}^{R1}\}$.

The objective function (5a) minimizes the total cost of redispatching energy and deploying reserve minus the revenue from the deviation demand in each period and each scenario. Equation (5b) enforces the real-time power balance at each bus. Constraints (5c)–(5f) limit the power of each conventional generator that can be sold into the real-time market. The amount of wind power that can be sold in the real-time market in each scenario is constrained by the forecasted wind power in the scenario, as described by (5g). The bounds of the deviated demand in each scenario are represented by constraint (5h). The deployed up and down reserves are bounded by the scheduled up and down reserves in the day-ahead market, respectively, as expressed in (5i) and (5j), respectively. Constraint (5k) imposes the transmission capacity limits of each power line. The voltage angle limits of each bus are expressed in constraint (5l). The reference bus is selected in (5m).

The wind power trading in the real-time market is different from the conventional power producers due to the uncertainty in the wind power production. The wind power producer may fail to fulfill the productions settled in the day-ahead market and is forced to correct its negative deviation in the real-time market. Meanwhile, the wind power producer can bid the extra power into the real-time market if the deviation is positive. The rescheduled wind power is constrained by (5g) for both cases. Since the day-ahead market is cleared prior to the real-time market, the decision variables R_{it}^U and R_{it}^D of the problem (2) and $p_{bit\omega}^{CD}$, $p_{bjt\omega}^{WD}$, and $p_{ldt\omega}^{LD}$ of the problem (4) are considered to be parameters in the problem (5).

IV. Model Conversion

To facilitate the solution process, the bilevel programming problem (3)–(5) is transferred into an equivalent single-level MPEC problem through the KKT conditions [13] of the lower level problems (4) and (5).

A. Optimality Condition of (4)

The problem (4) is transferred by its KKT condition as follows:

$$\lambda_{bit\omega}^{CD}-\lambda_{mt\omega}^{DA}+\mu_{bit\omega}^{C\max}-\mu_{bit\omega}^{C\min}=0\quad\forall b,i\in\Psi_m^I,t,\omega \tag{6a}$$

$$\lambda_{bwt\omega}^{WD}-\lambda_{mt\omega}^{DA}+\mu_{bjt\omega}^{W\max}-\mu_{bjt\omega}^{W\min}=0\quad\forall b,j\in\Psi_m^W,t,\omega \tag{6b}$$

$$-\lambda_{ldt}^{LD}+\lambda_{mt\omega}^{DA}+\mu_{ldt\omega}^{L\max}-\mu_{ldt\omega}^{L\min}=0\quad\forall l,d\in\Psi_m^D,t,\omega \tag{6c}$$

$$\sum_{n\in\Phi_m}B_{mn}\left(\lambda_{mt\omega}^{DA}-\lambda_{nt\omega}^{DA}+\beta_{mnt\omega}^{D\max}-\beta_{nmt\omega}^{D\max}+\beta_{mnt\omega}^{D\min}\right.$$
$$\left.-\beta_{nmt\omega}^{D\min}\right)+\theta_{mt\omega}^{D\max}-\theta_{mt\omega}^{D\min}+\theta_{t\omega}^{D1}|_{m=1}=0\quad\forall m,t,\omega \tag{6d}$$

$$\text{(4b)} \tag{6e}$$

$$0\le p_{bit\omega}^{CD}\perp\mu_{bit\omega}^{C\min}\ge0\quad\forall b,i,t,\omega \tag{6f}$$

$$0\le\left(p_{bit}^{CD\max}-p_{bit\omega}^{CD}\right)\perp\mu_{bit\omega}^{C\max}\ge0\quad\forall b,i,t,\omega \tag{6g}$$

$$0\le p_{bjt}^{WD}\perp\mu_{bjt\omega}^{W\min}\ge0\quad\forall b,w,t,\omega \tag{6h}$$

$$0\le\left(P_{jtb}^{Wf}-p_{bjt\omega}^{WD}\right)\perp\mu_{bjt\omega}^{W\max}\ge0,b=1\quad\forall j,t,\omega \tag{6i}$$

$$0\le\left(P_{jtb}^{Wf}-P_{jt(b-1)}^{Wf}-p_{bjt\omega}^{WD}\right)\perp\mu_{bjt\omega}^{W\max}\ge0\quad\forall b\ge2,j,t,\omega \tag{6j}$$

$$0\le p_{ldt\omega}^{LD}\perp\mu_{ldt\omega}^{L\min}\ge0\quad\forall l,d,t,\omega \tag{6k}$$

$$0\le\left(p_{ldt}^{LD\max}-p_{ldt\omega}^{LD}\right)\perp\mu_{ldt\omega}^{L\max}\ge0\quad\forall l,d,t,\omega \tag{6l}$$

$$0\le\left[C_{mn}^{\max}+B_{mn}\left(\delta_{mt\omega}^{D}-\delta_{nt\omega}^{D}\right)\right]\perp\beta_{mnt\omega}^{D\min}$$
$$\ge0\quad\forall m,n\in\Phi_m,t,\omega \tag{6m}$$

$$0\le\left[C_{mn}^{\max}-B_{mn}\left(\delta_{mt\omega}^{D}-\delta_{nt\omega}^{D}\right)\right]\perp\beta_{mnt\omega}^{D\max}$$
$$\ge0\quad\forall m,n\in\Phi_m,t,\omega \tag{6n}$$

$$0\le(\delta_m^{\min}+\delta_{mt\omega}^{D})\perp\theta_{mt\omega}^{D\min}\ge0\quad\forall m,t,\omega \tag{6o}$$

$$0\le(\delta_m^{\max}-\delta_{mt\omega}^{D})\perp\theta_{mt\omega}^{D\max}\ge0\quad\forall m,t,\omega \tag{6p}$$

where $\perp$ denotes complementarity operation.

B. Optimality Condition of (5)

Similarly, the problem (5) is transferred by its KKT condition as follows:

$$\lambda_{it}^{CR+} - \lambda_{mt\omega}^{RT} + \mu_{it\omega}^{\max +} - \mu_{it\omega}^{\min +} + \mu_{it\omega}^{CR+} = 0 \quad \forall i \in \Psi_m^I, t, \omega \tag{7a}$$

$$-\lambda_{it}^{CR-} + \lambda_{mt\omega}^{RT} + \mu_{it\omega}^{\max -} - \mu_{it\omega}^{\min -} + \mu_{it\omega}^{CR-} = 0 \quad \forall i \in \Psi_m^I, t, \omega \tag{7b}$$

$$\lambda_{jt\omega}^{WR} - \lambda_{mt\omega}^{RT} + \mu_{jt\omega}^{WR\max} - \mu_{jt\omega}^{WR\min} = 0 \quad \forall j \in \Psi_m^W, t, \omega \tag{7c}$$

$$\lambda_{it}^{RU} - \lambda_{mt\omega}^{RT} + \varphi_{it\omega}^{U\max} - \varphi_{it\omega}^{U\min} = 0 \quad \forall i \in \Psi_m^I, t, \omega \tag{7d}$$

$$\lambda_{it}^{RD} + \lambda_{mt\omega}^{RT} + \varphi_{it\omega}^{D\max} - \varphi_{it\omega}^{D\min} = 0 \quad \forall i \in \Psi_m^I, t, \omega \tag{7e}$$

$$-\lambda_{dt\omega}^{LR} + \lambda_{mt\omega}^{RT} + \mu_{it\omega}^{LR\max} - \mu_{it\omega}^{LR\min} = 0 \quad \forall l, d \in \Psi_m^D, t \tag{7f}$$

$$\sum\nolimits_{n \in \Phi_m} B_{mn} \left(\lambda_{mt\omega}^{RT} - \lambda_{nt\omega}^{RT} + \beta_{mnt\omega}^{R\max} - \beta_{nmt\omega}^{R\max} + \beta_{mnt\omega}^{R\min} - \beta_{nmt\omega}^{R\min}\right) + \theta_{mt\omega}^{R\max} - \theta_{mt\omega}^{R\min} + \theta_t^{R1}|_{m=1} = 0 \quad \forall m, t, \omega \tag{7g}$$

$$(5b) \tag{7h}$$

$$0 \le P_{it\omega}^{CR+} \perp \mu_{it\omega}^{\min +} \ge 0 \quad \forall i, t, \omega \tag{7i}$$

$$0 \le \left(P_i^{\max +} - P_{it\omega}^{CR+}\right) \perp \mu_{it\omega}^{\max +} \ge 0 \quad \forall i, t, \omega \tag{7j}$$

$$0 \le P_{it\omega}^{CR-} \perp \mu_{it\omega}^{\min -} \ge 0 \quad \forall i, t, \omega \tag{7k}$$

$$0 \le \left(P_i^{\max -} - P_{it\omega}^{CR-}\right) \perp \mu_{it\omega}^{\max -} \ge 0 \quad \forall i, t, \omega \tag{7l}$$

$$0 \le \left(P_i^{\max -} - \sum\nolimits_b p_{bit}^{CD} - P_{it\omega}^{CR+}\right) \perp \mu_{it\omega}^{CR+} \ge 0 \quad \forall i, t, \omega \tag{7m}$$

$$0 \le \left(\sum\nolimits_b p_{bit}^{CD} - P_{it\omega}^{CR-}\right) \perp \mu_{it\omega}^{CR-} \ge 0 \quad \forall i, t, \omega \tag{7n}$$

$$0 \le \left(\sum\nolimits_b p_{bjt}^{WD} + P_{jt\omega}^{WR}\right) \perp \mu_{jt\omega}^{WR\min} \ge 0 \quad \forall j, t, \omega \tag{7o}$$

$$0 \le \left(P_{jtb}^{Wf} - \sum\nolimits_b p_{bjt}^{WD} - P_{jt\omega}^{WR}\right) \perp \mu_{jt\omega}^{WR\max} \ge 0 \quad \forall j, t, \omega \tag{7p}$$

$$\begin{cases} 0 \le P_{dt\omega}^{LR} \perp \mu_{dt\omega}^{LR\min} \ge 0 \quad \forall d, t, \omega, \text{if} P_{dt\omega}^{LRf} \ge 0 \\ 0 \le \left(P_{dt\omega}^{LRf} - P_{dt\omega}^{LR}\right) \perp \mu_{dt\omega}^{LR\min} \ge 0 \quad \forall d, t, \omega, \text{if} P_{dt\omega}^{LRf} < 0 \end{cases} \tag{7q}$$

$$\begin{cases} 0 \le \left(P_{dt\omega}^{LRf} - P_{dt\omega}^{LR}\right) \perp \mu_{dt\omega}^{LR\max} \ge 0 \quad \forall d, t, \omega, \text{if} P_{dt\omega}^{LRf} \ge 0 \\ 0 \le P_{dt\omega}^{LR} \perp \mu_{dt\omega}^{LR\max} \ge 0 \quad \forall d, t, \omega, \text{if} P_{dt\omega}^{LRf} < 0 \end{cases} \tag{7r}$$

$$0 \le r_{it\omega}^U \perp \varphi_{it\omega}^{U\min} \ge 0 \quad \forall i, t, \omega \tag{7s}$$

$$0 \le \left(R_{it}^U - r_{it\omega}^U\right) \perp \varphi_{it\omega}^{U\max} \ge 0 \quad \forall i, t, \omega \tag{7t}$$

$$0 \le r_{it\omega}^D \perp \varphi_{it\omega}^{D\min} \ge 0 \quad \forall i, t, \omega \tag{7u}$$

$$0 \le \left(R_{it}^D - r_{it\omega}^D\right) \perp \varphi_{it\omega}^{D\max} \ge 0 \quad \forall i, t, \omega \tag{7v}$$

$$0 \le \left[C_{mn}^{\max} + B_{mn}\left(\delta_{mt\omega}^R - \delta_{nt\omega}^R\right)\right] \perp \beta_{mnt}^{R\min} \ge 0 \quad \forall m, n \in \Phi_m, t \tag{7w}$$

$$0 \le \left[C_{mn}^{\max} - B_{mn}\left(\delta_{mt\omega}^R - \delta_{nt\omega}^R\right)\right] \perp \beta_{mnt}^{R\max} \ge 0 \quad \forall m, n \in \Phi_m, t \tag{7x}$$

$$0 \le (\delta_m^{\min} + \delta_{mt\omega}^R) \perp \theta_{mt\omega}^{R\min} \ge 0 \quad \forall m, t, \omega \tag{7y}$$

$$0 \le (\delta_m^{\max} - \delta_{mt\omega}^R) \perp \theta_{mt\omega}^{R\max} \ge 0 \quad \forall m, t, \omega \tag{7z}$$

C. Reformulate MPEC as an MILP

The MPEC problem having the objective function (3a) and subject to constraints (3b)–(3e), (6), and (7) is a nonlinear programming problem, where the nonlinearities come from the following three main sources. By linearizing the nonlinear terms, the MPEC problem is converted into an MILP problem, which can be solved effectively.

1) The $\sum_{jb} \lambda_{(m:j\in\Psi_m^W)t\omega}^{DA} p_{bjt\omega}^{WD}$ term in (3a).

According to (6b), (6h), (6i), (6j), and the strong duality theorem, this term can be linearized to (8) [29].

$$\begin{aligned} &\sum\nolimits_{jb} \lambda_{(m:j\in\Psi_m^W)t\omega}^{DA} p_{bjt\omega}^{WD} \\ &= \sum\nolimits_{jb} \left(\lambda_{bjt\omega}^{WD} + \mu_{bjt\omega}^{W\max} - \mu_{bjt\omega}^{W\min}\right) p_{bjt\omega}^{WD} \\ &= -\sum\nolimits_{bi} \lambda_{bit\omega}^{CD} p_{bit\omega}^{CD} - \sum\nolimits_{bi} p_{bit}^{CD\max} \mu_{bit\omega}^{C\max} \\ &\quad + \sum\nolimits_{ld} \lambda_{ldt}^{LD} p_{ldt\omega}^{LD} - \sum\nolimits_{ld} p_{ldt}^{LD\max} \mu_{ldt\omega}^{L\max} \\ &\quad - \sum\nolimits_{m(n\in\Phi_m)} C_{mn}^{\max}\left(\beta_{mnt\omega}^{D\max} + \beta_{mnt\omega}^{D\min}\right) \\ &\quad - \sum\nolimits_m \left(\delta_m^{\max}\theta_{mt\omega}^{D\max} - \delta_m^{\min}\theta_{mt\omega}^{D\min}\right) \end{aligned} \tag{8}$$

2) The $\sum_j \lambda_{(m:j\in\Psi_m^W)t\omega}^{RT} p_{jt\omega}^{WR}$ term in (3a).

Similar to (8), according to (7c), (7o), (7p), and the strong duality theorem, this term can be linearized to (9) [29].

$$\begin{aligned} &\sum\nolimits_j \lambda_{(m:j\in\Psi_m^W)t\omega}^{RT} p_{jt\omega}^{WR} \\ &= \sum\nolimits_j \left(\lambda_{jt\omega}^{WD} + \mu_{jt\omega}^{WR\max} - \mu_{jt\omega}^{WR\min}\right) p_{jt\omega}^{WR} \\ &= -\sum\nolimits_i \left(\lambda_{it}^{CR+} P_{it\omega}^{CR+} - \lambda_{it}^{CR-} P_{it\omega}^{CR-}\right) \\ &\quad - \sum\nolimits_i \left(\lambda_{it}^{RU} r_{it\omega}^U + \lambda_{it}^{RD} r_{it\omega}^D\right) \\ &\quad + \sum\nolimits_d \lambda_{dt\omega}^{LR} P_{dt\omega}^{LR} \\ &\quad - \sum\nolimits_i \left(P_i^{\max +}\mu_{it\omega}^{\max +} + P_i^{\max -}\mu_{it\omega}^{\max -}\right) \\ &\quad - \sum\nolimits_i \mu_{it\omega}^{CR+}\left(P_i^{\max} - \sum\nolimits_b p_{bit}^{CD}\right) \\ &\quad - \sum\nolimits_i \mu_{it\omega}^{CR-} \sum\nolimits_b p_{bit}^{CD} \\ &\quad - \sum\nolimits_i \left(\varphi_{it\omega}^{U\max} R_{it}^U + \varphi_{it\omega}^{D\max} R_{it}^D\right) \\ &\quad - \begin{cases} \sum_d P_{dt\omega}^{LRf} \mu_{dt\omega}^{LR\max}, \text{if} P_{dt\omega}^{LRf} \ge 0 \\ \sum_d P_{dt\omega}^{LRf} \mu_{dt\omega}^{LR\min}, \text{if} P_{dt\omega}^{LRf} < 0 \end{cases} \\ &\quad - \sum\nolimits_{m(n\in\Phi_m)} C_{mn}^{\max}\left(\beta_{mnt\omega}^{R\max} + \beta_{mnt\omega}^{R\min}\right) \\ &\quad - \sum\nolimits_m \left(\delta_m^{\max}\theta_{mt\omega}^{R\max} - \delta_m^{\min}\theta_{mt\omega}^{R\min}\right). \end{aligned} \tag{9}$$

There is still a nonlinear term $\left(\mu_{it\omega}^{CR+} - \mu_{it\omega}^{CR-}\right)\sum_b p_{bit}^{CD}$ in (9). It can be linearized using the method in [30].

3) The MPEC model includes the nonlinear complementarity constraints (6f)–(6p) and (7i)–(7z). According to [27], the complementarity constraint in the form of $0 \leq P \perp Q \geq 0$ can be replaced by the following formulation:

$$P \geq 0, Q \geq 0, P \leq \mu M, Q \leq (1-\mu) M, \mu \in \{0,1\} \tag{10}$$

where M is a sufficiently large constant. Its value can be different for different complementarity constraints. Usually, M is set to be $(\text{dual variable} + 1) \times 100$.

V. Case Studies and Results

The proposed model is tested using the IEEE Reliability Test System [31], which has ten conventional power producers and one wind power producer. The data of the conventional generators are obtained from [32]. The total installed wind capacity $P^{W\max}$ of the only wind power producer is 1000 MW, which is approximately 23% of the total installed generation capacity in the system. In all case studies except for those explained specifically, all wind power generating units are located at bus 8 and the wind power producer is a strategic player in both the day-ahead and the real-time markets. The wind power data are obtained from the National Renewable Energy Laboratory website [33]. The historical data of the real-time demand are obtained from the PJM market [34]. The sensitivity analysis of the day-ahead LMPs with respect to the bidding prices of each conventional power producer will be conducted in Section V-D. The uncertainties of the bidding prices of the selected conventional power producers will then be considered as additional scenarios in the model for case studies in Section V-D, but are not included in other case studies in this section for simplicity. The parameters α and β in (3a) are set to be 0.95 and 0, respectively. λ^{CapD} and λ^{CapR} are set to be $\$1000/\text{MWh}$. In all of the case studies, the MILP problem is solved using Gurobi 5.5 in MATLAB [35].

The autoregressive integrated moving average (ARIMA) model [4] is used to generate 5000 scenarios of wind power and real-time demand, respectively. Then, the scenario reduction method [26] is applied to reduce the number of scenarios for the wind power and real-time demand. In order to determine the best number of scenarios for the case studies, the objective value of (3a) and the CVaR (when $\beta = 0.1$) of the wind power producer are calculated using the MILP model for different number of scenarios. As shown in Fig. 2, both the objective value and CVaR initially decrease significantly when the number of scenarios increases, but only change slightly after the number of scenarios is larger than 32. For example, the percentage changes of both the objective value and the CVaR by increasing the scenario number from 64 to 128 are less than 0.7%. Therefore, 64 scenarios are selected for the case studies in this paper as a tradeoff between the accuracy and computational cost.

Table I lists the information (values and probabilities) of the resulting eight wind power scenarios and eight real-time demand scenarios for a certain hour, where a real-time demand scenario is described by the ratio of the forecasted real-time demand to the day-ahead demand.

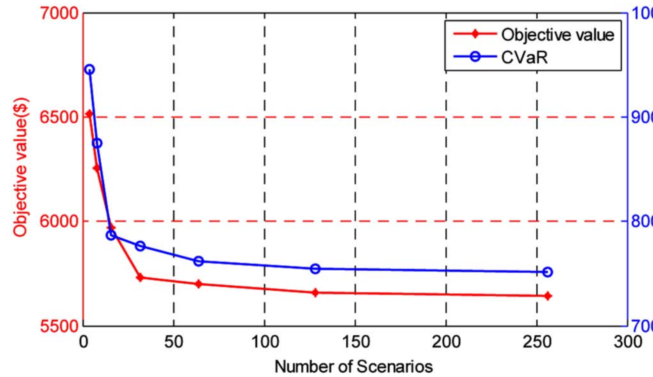

Fig. 2. Objective value and CVaR (when $\beta = 0.1$) of the wind power producer versus the number of scenarios.

TABLE I
SCENARIO INFORMATION

Wind power scenario (MW)	Probability	Real-time demand scenario	Probability
221.76	0.021	0.712	0.038
309.21	0.052	0.784	0.071
393.67	0.0917	0.890	0.092
466.65	0.213	0.913	0.158
521.90	0.101	0.956	0.175
652.34	0.391	1.089	0.126
765.52	0.128	1.125	0.201
803.24	0.0848	1.236	0.1390

TABLE II
PROFITS OF THE WIND POWER PRODUCER IN FOUR CASES

Case	Expected profit ($)	Decrement of expected profit
a	5687.4618	0
b	5196.8437	8.63%
c	2875.6691	49.44%
d	2501.2373	56.02%

A. Comparison of Strategic and Nonstrategic Wind Power Producers

Four cases are compared in this study: (a) the wind power producer is a strategic player in both the day-ahead and real-time markets; (b) the wind power producer is a strategic player in the day-ahead market only; (c) the wind power producer is a strategic player in the real-time market only; and (d) the wind power producer is a nonstrategic player in both the day-ahead and the real-time markets. The bidding prices will be set to be zero for a nonstrategic wind power producer in the market. Table II shows the profits of the wind power producer in the four cases and the percentage decreases in the expected profit of the last three cases with respect to the first case. The wind power producer achieves the highest profit by being a strategic player in both the day-ahead and the real-time markets. Moreover, the wind power producer obtains more profit in Case (b) than in Case (c), which suggests that the day-ahead market has more influence on the wind power producer than the real-time market.

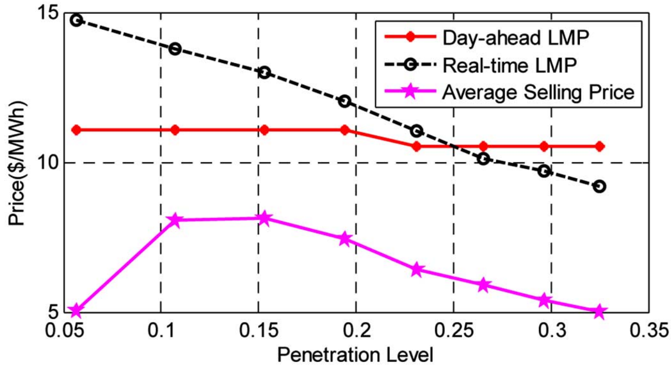

Fig. 3. Day-ahead and average real-time LMPs at bus 8 and average selling price of the wind power producer for different wind power penetration levels.

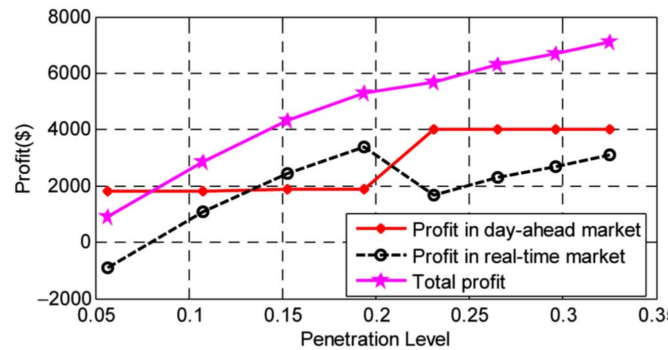

Fig. 4. Day-ahead, real-time, and total profits of the wind power producer for different penetration levels of wind power.

B. Impact of Wind Power Penetration Level

In this study, the installed wind power capacity is changed from 200 (5% penetration) to 1600 MW (33% penetration) with an increment of 200 MW. No capacity limits are imposed on the transmission constraints. The day-ahead and average real-time LMPs of the 64 scenarios at bus 8 and the average selling price of the wind power producer are shown in Fig. 3 for different wind power penetration levels.

Due to the fact that wind power has no fuel cost, selling wind power into the market will lower the LMP. As shown in Fig. 3, both the day-ahead LMP and the average real-time LMP decrease as the penetration level of wind power increases. However, due to the effect of the uncertainties in the real-time market, the real-time LMP is more sensitive than the day-ahead LMP to the changes of the demand and wind power supply. Therefore, the rate of decrease in the average real-time LMP is much greater than that of the average day-ahead LMP. When the penetration level is relatively low (5%–15%), the average selling price of wind power increases with the increase in the wind power penetration level. At these penetration levels, since the real-time LMP is much higher than the day-ahead LMP, selling more wind power into the real-time market will increase the average selling price. However, when the penetration level is relatively high (15%–32%), the average selling price of wind power decreases with the increase in the wind penetration level. At these penetration levels, since the real-time LMP decreases faster than the day-ahead LMP and is even lower than the day-ahead LMP when the penetration level becomes higher than 25%, selling the extra wind power into the real-time market will decrease the average selling price.

As can been seen more clearly from Fig. 4, the profit of the wind power producer in the day-ahead market stays almost the same at first, then increases dramatically, and finally stabilizes at a certain value when the penetration level increases. The cause of this result is explained as follows. When the penetration level of wind power is below 18%, the wind power producer does not have enough market power to influence the day-ahead LMPs. Therefore, the day-ahead LMP stays constant when the wind power penetration level changes within 18%. Moreover, when the wind power penetration level changes, the load demand in the day-ahead market does not change. Therefore, the amounts of power bid into the day-ahead market by the wind producer and the conventional generating units almost do not change. As a result, the profit of the wind producer in the day-ahead market almost does not change. The results also show that the wind power producer intends to sell more power into the real-time market to gain more profit because the real-time LMP is higher than the day-ahead LMP. This, however, results in a decline of the real-time price. As the wind power penetration level goes higher, the day-ahead LMP decreases dramatically; but, the profit of the wind producer obtained from the day-ahead market still increases because more power is sold into the day-ahead market. However, the system's ability to consume wind power in the day-ahead market is limited. As the wind power penetration level reaches 25%, further increasing the penetration level only results in a slight change in the day-ahead LMP and a slight increase in the wind power sold into the day-ahead market. Therefore, the day-ahead profit curve is almost constant as the wind power penetration level goes beyond 25%.

The profit in the real-time market increases first until the penetration level reaches 18%. Beyond this penetration level, the real-time profit decreases when the day-ahead profit increases and then increases, but is always below the day-ahead profit when the penetration level exceeds 21%. As the real-time price decreases to a certain level, the wind power producer will not sell all of its extra power into the real-time market to prevent further decrease in the real-time price and possible decrease in the total profit. As a result, some of the wind power generation capacity will be wasted as the wind power penetration level goes high. Therefore, it is important for the wind power producers to choose their installation capacities in a certain system. For example, in [36], the authors proposed a bilevel model to determine the optimal investment for a strategic wind power investor and concluded that the strategic behavior would increase the profit of the wind power investor when compared to the price-taker behavior. As Fig. 4 shows, the total profit of the wind producer increases with the wind penetration level.

C. Impact of Transmission Constraint

In this study, the wind power capacity is 1000 MW. The proposed model is solved to obtain the optimal bidding strategy for the wind producer for four cases: (a) no capacity limits are imposed on any transmission lines; and a capacity limit of (b) 190 MW, (c) 100 MW, and (d) 30 MW is imposed on the

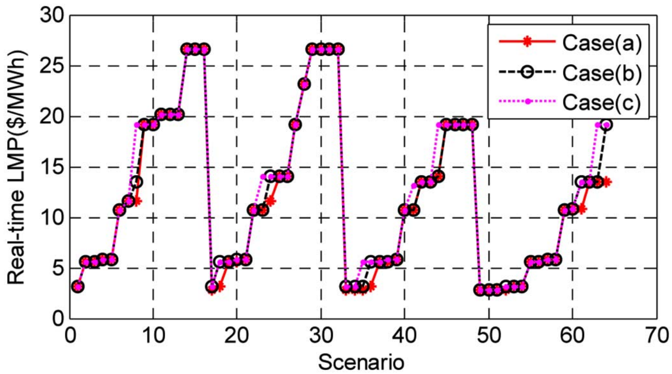

Fig. 5. Real-time LMPs at bus 8 in Cases (a), (b), and (c) in different scenarios.

TABLE III
PROFITS OF THE WIND PRODUCER AND DAY-AHEAD LMP AT BUS 8 IN DIFFERENT CASES

Case	Profit in day-ahead market ($)	Day-ahead LMP at bus 8 ($/MWh)	Profit in real-time market ($)	Total profit ($)
a	4012.71	10.66	1674.7518	5687.4618
b	3098.45	10.68	2813.6867	5912.1367
c	1796.23	11.09	3470.8958	5267.1258
d	1756.37	10.66	2151.8819	3908.2519

transmission line 8–9. Fig. 5 compares the real-time LMPs at bus 8 in different scenarios for Cases (a), (b), and (c). Case (d) is not plotted because the real-time LMPs of Cases (c) and (d) are the same. The profits of the wind power producer in the day-ahead and real-time markets, the total profit of the wind producer, and the day-ahead LMP at bus 8 for different cases are given in Table III.

When no capacity limits are imposed on the transmission lines, the power flow through line 8–9 is 75 MW in the day-ahead market and maximally 292 MW in the real-time market. As shown in Fig. 4, when the transmission capacity of line 8–9 is limited to 190 MW [Case (b)], the real-time LMP in Scenario 64 is higher than that in Case (a). Although the amount of wind power sold into the day-ahead market in Case (b) is lower than that in Case (a), the total profit in Case (b) is higher than that in Case (a) owing to the higher real-time LMPs. Limiting the transmission capacity to 100 MW in Case (c) will further increase the real-time LMP when compared to Case (b), as shown in Fig. 5. As a consequence, less amount of wind power will be sold in the day-ahead market in Case (c) when compared with Cases (a) and (b). However, the increase in the real-time LMP will not be able to compensate for the profit loss due to the decrease in the wind power sold in the day-ahead market caused by the transmission congestion. In Case (d), the profit in the day-ahead market increases slightly compared to Case (c) owing to the increase in the day-ahead LMP. However, the total profit decreases dramatically compared with the previous three cases due to the small transmission capacity limit.

Based on the four case studies, it can conclude that transmission congestion can be sometimes beneficial to wind power producers and can be used as a strategic mechanism to increase their profits.

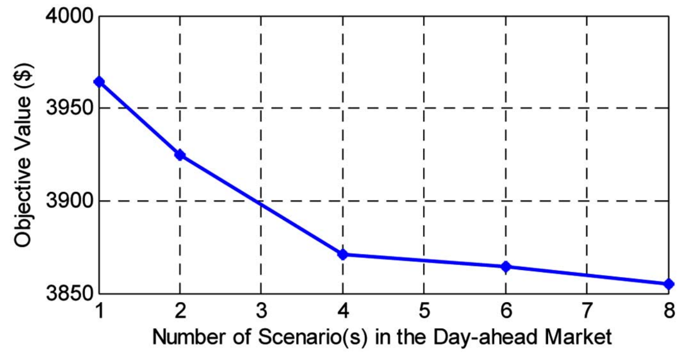

Fig. 6. Objective value of the wind power producer versus the number of scenarios in the day-ahead market.

D. Impact of the Uncertainties of Other Producers' Bidding Strategies

In this case, the wind power producer's capacity is 500 MW, and no capacity limits are imposed on the transmission lines. The LMP sensitivity analysis is carried out to select the strategic producers whose bidding prices will have nonnegligible impacts on the LMP at the bus (i.e., bus 8) where the wind power units are located and the LMP sensitivities to all other producers' bidding prices are defined as follows:

$$\frac{\partial \lambda_{mt}^{DA}}{\partial \lambda_{bit}^{CD}} \tag{11}$$

for all $i \in I, b \in B, m = 8$.

The LMP sensitivity analysis result shows that the LMP λ_{8t}^{DA}in the period t is most sensitive to the bidding price of the first block of the conventional power producer 1 since $\lambda_{1,1t}^{CD}$ is fairly close to the cleared LMP, while the LMP sensitivities to all of the other conventional power producers expressed by (11) are close to zero. Thus, only the uncertainty of the conventional power producer 1's bidding strategy is considered via scenarios in the model.

The similar scenario generation and reduction process used for the real-time demand and wind power production is applied to the bidding price of the first block of the conventional power producer 1. Fig. 6 shows that the objective value of the wind power producer decreases as the number of scenarios of the conventional power producer 1's bidding price in the day-ahead market increases. When the number of scenarios increases from 6 to 8, the objective value only changes by 0.2%. Therefore, six additional scenarios are incorporated in the day-ahead market clearing model to characterize the uncertainty of the bidding price of the first block of the conventional power producer 1. The total number of scenarios of the real-time market clearing model increases to 384 then.

The six scenarios are sorted in a sequence that the bidding price of the first block of the conventional power producer 1 increases. The day-ahead LMP at bus 8, the expected profits of the wind power producer in the day-ahead and real-time markets, and the expected total profit are calculated using the proposed model with the added six scenarios and shown in Fig. 7. The day-head LMP at bus 8 increases as the bidding price of the conventional power producer 1 increases. The wind

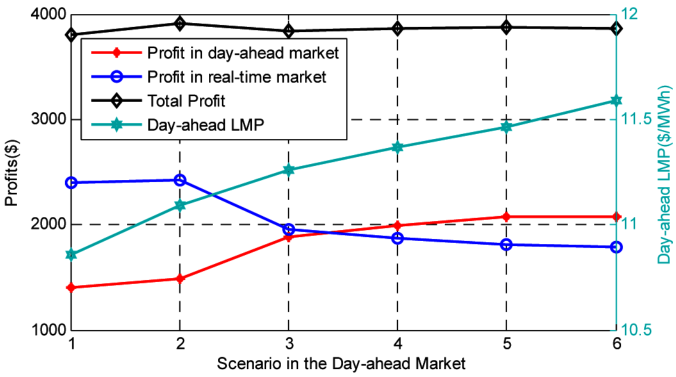

Fig. 7. Expected profits of the wind power producer in the day-ahead and real-time markets, the expected total profit, and the day-ahead LMP at bus 8 in different scenarios of the day-ahead market.

TABLE IV
PROFITS OF EACH WIND FARM AND DAY-AHEAD LMP IN DIFFERENT CASES

Case No. \ Profit	Day-ahead market ($)		Real-time market ($)		Total ($)
	Wind farm No.		Wind farm No.		
	1	2	1	2	
a	4762.34	2218.56	−2318.90	1283.01	5945.01
b	4762.34	2218.56	−2783.24	986.36	5184.02
c	1982.35	1134.21	−1702.67	701.56	2115.45

power producer bids more power and gains more profit in the day-ahead market and less profit in the real-time market as the day-ahead LMP increases. Even though the bidding prices of the conventional power producer 1 in difference scenarios vary considerably (the difference between Scenario 6 and Scenario 1 is 10%), the total profits of the wind power producer in different scenarios are relatively stable and the maximum variation is only 2.8%. These results show that the wind power producer is capable of handling the uncertainties of other power producers' bidding strategies in a certain range.

E. Wind Power Generating Units at Different Locations

In this case, it is assumed that the wind power producer has two wind farms with the same installed capacity of 500 MW located at different buses, i.e., buses 7 (wind farm 1) and 8 (wind farm 2). The proposed model is solved for three cases: (a) no capacity limits are imposed on any transmission lines; and a capacity limit of (b) 100 MW and (c) 30 MW is imposed on the transmission line 7–8. The profits gained from the day-ahead and real-time markets and the total profit of each wind farm are shown in Table IV.

The negative profit of wind farm 1 in the real-time market indicates that it has to purchase the deficit power from the real-time market. Wind farm 1 gains profit from the day-ahead market and has loss in the real-time market, while wind farm 2 gains profits from both the day-ahead and real-time markets. This result indicates that wind power generating units in different locations owned by the same producer may behave differently in the market even their LMPs are the same. Since bus 7 is only connected to the system through line 7–8, if wind farm 1 has deficit power in the real-time market, it can

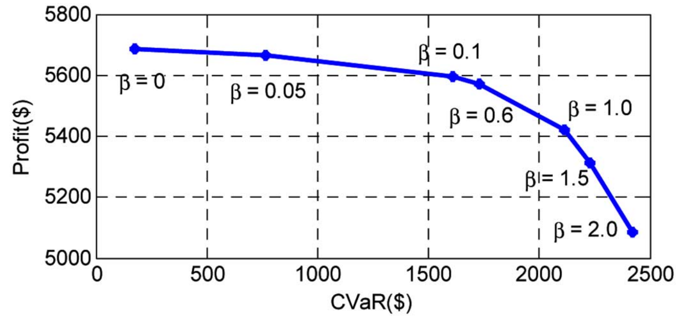

Fig. 8. Expected total profit and CVaR of the wind power producer for different values of β.

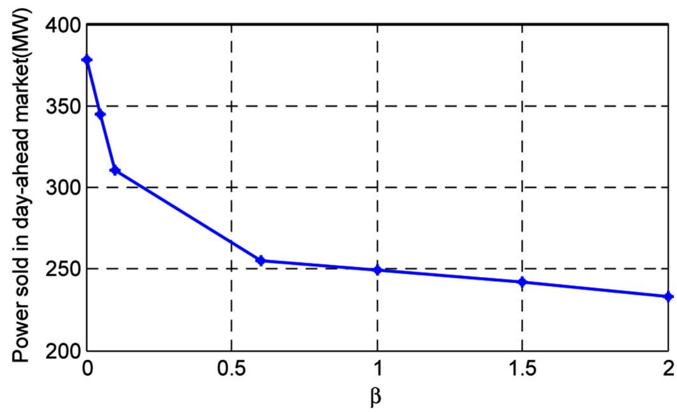

Fig. 9. Wind power sold into the day-ahead market for different values of β.

only purchase power from wind farm 2 to cover the deficiency. As transmission limits are imposed to line 7–8, compared to Case (a), the total profit of wind farm 1 decreases to 19.0% in Case (b) and 88.55% in Case (c), while the total profit of wind farm 2 decreases to 12.85% in Case (b) and 64.42% in Case (c). The results show that the transmission congestion has a greater effect on wind farm 1 than wind farm 2. This case study shows that the proposed model is also effective for obtaining the optimal bidding strategies for wind power producers with multiple wind farms in different locations.

F. Impact of Risk Management

In this study, the installed wind power is 1000 MW. The proposed model is solved for different values of β in (3a). As shown in Fig. 8, the expected total profit of the wind power producer decreases and the CVaR increases with the increase of β. The wind bidding capacity in the day-ahead market decreases when β increases, as plotted in Fig. 9. These results are expected. A higher β indicates that the wind power producer is willing to take less risk by selling less power into the day-ahead market. As a consequence, the chance of the wind power producer to counter a negative deviation in the real-time market decreases. The bidding curves of the wind power producer in the day-ahead market for three selected values of β in Fig. 10 also show this trend: the bidding capacity decreases, while the bidding price increases as β increases. Moreover, the expected total profit and bidding strategy are quite sensitive to the value of β when it is between 0 and 1.0, and its value should

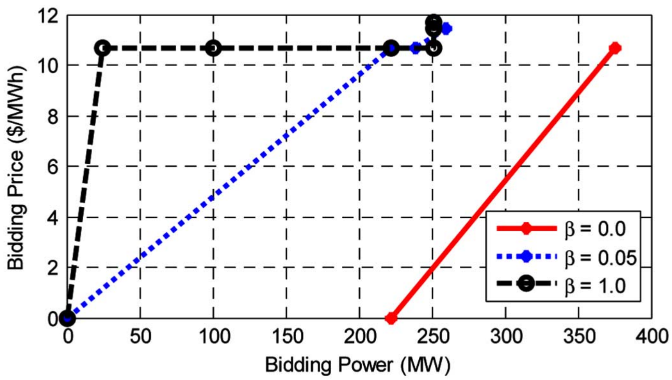

Fig. 10. Day-ahead bidding curves of the wind power producer for different values of β.

TABLE V
COMPARISON OF COMPUTATIONAL TIME AND COMPLEXITY FOR DIFFERENT CASES

	Without transmission constraint	With transmission constraints
Computational time (s)	1111.19	6067.04
Equal constraints	34672	34672
Unequal constraints	5672	5866
Continuous variables	7914	8298
Binary variables	4440	4632

be selected carefully by the wind power producer. These results show the significance of risk management for the wind power producer to obtain the optimal bidding strategy.

G. Computational Issue

The computer used for simulation studies has a 3.16-GHz, 4-core CPU and a 16-GB RAM. The computational times and the numbers of constraints and variables of using the proposed model with and without transmission constraints for the case studies are compared in Table V. The proposed model can be used for systems of larger sizes in real-world applications where much more powerful computer workstations or clusters are commonly used.

VI. CONCLUSION

As the wind power penetration level goes higher in the electricity market, the wind power producer with a large installed capacity can no longer be considered as a price-taker when generating its optimal bidding strategy. This paper has proposed a model considering the strategic bidding behavior of a wind power producer in the electricity market. In the model, the day-ahead and real-time LMPs are not input data, but variables that are influenced by the wind power producer. The optimal bidding strategy of the wind power producer has been generated by a bilevel stochastic optimization model, which has been converted into a single-level MILP problem using the duality theory and KKT condition to facilitate solving the model. Case studies have been performed for the IEEE Reliability Test System with a strategic wind producer. Results have shown that as the wind penetration level goes higher, the day-ahead and real-time LMPs decrease. The network congestion has inevitable impact on the bidding strategy and can be used as a strategic mechanism to further increase the profit of the wind power producer. The LMP sensitivity analysis has been conducted to help the wind power producer determine what other strategic conventional power producers' bidding prices should be considered as uncertainties in the proposed model via scenarios. The proposed model is also effective for wind power producers with generating units in different locations. Due to the uncertainty of wind power production and real-time demand, the optimal bidding strategy of the wind power producer is sensitive to the risk parameters, which should be chosen carefully by the decision-makers. Further research will be conducted to study the optimal bidding strategies for multiple strategic players in an electricity market.

APPENDIX
PERTURBATION APPROACH FOR SENSITIVITY ANALYSIS

The day-ahead market clearing process (4) can be rewritten in the following compact form (12):

$$\min_{\boldsymbol{x}} z = f(\boldsymbol{x}, \boldsymbol{a}) \tag{12a}$$

Subject to

$$\boldsymbol{h}(\boldsymbol{x}, \boldsymbol{a}) = 0 : \boldsymbol{\lambda} \tag{12b}$$
$$g(\boldsymbol{x}, \boldsymbol{a}) \leq 0 : \boldsymbol{\mu} \tag{12c}$$

where z represents the objective function, the vector $\boldsymbol{x}$ includes all the primal decision variables, the vector $\boldsymbol{a}$ represents the bidding prices of the strategic conventional power producers, and $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ are the dual variables for equality and inequality constraints, respectively. In this paper, $\boldsymbol{\lambda}$ is the set of the LMP at each bus.

According to [25], by differentiating the KKT condition of problem (12), the following system of linear equations (13) is satisfied:

$$[\nabla_{\boldsymbol{x}} f(\boldsymbol{x}^*, \boldsymbol{a})]^T d\boldsymbol{x} + [\nabla_{\boldsymbol{a}} f(\boldsymbol{x}^*, \boldsymbol{a})]^T d\boldsymbol{a} - dz = 0 \tag{13a}$$

$$\begin{aligned}&\left[\nabla_{\boldsymbol{xx}} f(\boldsymbol{x}^*, \boldsymbol{a}) + \sum\nolimits_{\boldsymbol{r}}^{\boldsymbol{R}} \boldsymbol{\lambda}_r^* \nabla_{\boldsymbol{xx}} h_r(\boldsymbol{x}^*, \boldsymbol{a}) \right. \\ &\quad \left. + \sum\nolimits_{\boldsymbol{s}}^{\boldsymbol{S}} \mu_s^* \nabla_{\boldsymbol{xx}} g_s(\boldsymbol{x}^*, \boldsymbol{a})\right] dx \\ &+ \left[\nabla_{\boldsymbol{xa}} f(\boldsymbol{x}^*, \boldsymbol{a}) + \sum\nolimits_{\boldsymbol{r}}^{\boldsymbol{R}} \boldsymbol{\lambda}_r^* \nabla_{\boldsymbol{xa}} h_r(\boldsymbol{x}^*, \boldsymbol{a}) \right. \\ &\quad \left. + \sum\nolimits_{\boldsymbol{s}}^{\boldsymbol{S}} \mu_s^* \nabla_{\boldsymbol{xa}} g_s(\boldsymbol{x}^*, \boldsymbol{a})\right] d\boldsymbol{a} + \nabla_{\boldsymbol{x}} \boldsymbol{h}(\boldsymbol{x}^*, \boldsymbol{a}) d\boldsymbol{\lambda} \\ &+ \nabla_{\boldsymbol{x}} \boldsymbol{h}(\boldsymbol{x}^*, \boldsymbol{a}) d\boldsymbol{\lambda} = 0\end{aligned} \tag{13b}$$

$$[\nabla_{\boldsymbol{x}} \boldsymbol{h}(\boldsymbol{x}^*, \boldsymbol{a})]^T d\boldsymbol{x} + [\nabla_{\boldsymbol{a}} \boldsymbol{h}(\boldsymbol{x}^*, \boldsymbol{a})]^T d\boldsymbol{a} = 0 \tag{13c}$$
$$[\nabla_{\boldsymbol{x}} \boldsymbol{g}(\boldsymbol{x}^*, \boldsymbol{a})]^T d\boldsymbol{x} + [\nabla_{\boldsymbol{a}} \boldsymbol{g}(\boldsymbol{x}^*, \boldsymbol{a})]^T d\boldsymbol{a} = 0 \tag{13d}$$

where R and S are the total number of equality and inequality constraints. Then, $\frac{d\boldsymbol{\lambda}}{d\boldsymbol{a}}$, which is the sensitivity of the LMP at each bus to the bidding prices of the strategic conventional power producers, can be obtained by solving (13).

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