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Trading Wind Power in a Competitive Electricity Market Using Stochastic Programing and Game Theory

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***Abstract*—Wind power is one of the most rapidly growing clean and renewable energy sources. However, 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. Moreover, as a participant in a competitive electricity market, a wind power producer's behavior and profit will be influenced by other participants' behaviors. This paper proposes a model of using stochastic programming to generate optimal bidding strategies to maximize the total profits of wind and conventional power producers in both the energy market and a bilateral reserve market, where the reserve price is settled between wind and conventional power producers by using game theory. Case studies using real-world data for games in an electricity market with different types of players are performed to show the effectiveness of the proposed model.**

***Index Terms*—Bidding strategy, electricity market, game theory, stochastic programming, wind power.**

NOMENCLATURE

The most important notations used throughout the paper are listed below for quick reference.

Indices:

t	Index of time periods, running from 1 to N_T.
g	Index of conventional generating units of a power producer, running from 1 to N_G. $g=1$ for wind power producers.
ω, ω'	Index of scenarios, running from 1 to N_Ω.
i	Index of players, running from 1 to I.

Decision Variables:

P_{gt}^D	Power offered by a conventional unit g in the day-ahead market for a time period t.
P_{gt}^r	Power offered by a conventional unit g in the real-time market for a time period t.
P_{gt}^R	Power offered by a conventional unit g in the bilateral reserve settlement for a time period t.
P_{gt}^{ac}	Total actual power output of a conventional unit g for a time period t.
λ_t^R	Reserve price in a time period t.
W_t^D	Power offered by a wind producer in the day-ahead market for a time period t.
W_t^R	Power bidden by a wind producer in the bilateral reserve market for a time period t.
u_{gt}	State of a conventional unit g in a time period t, where $u=1$ means ON and $u=0$ means OFF.
ζ	Auxiliary variable used to compute the CVaR.
η_ω	Auxiliary variable used to compute the CVaR in a scenario.

Random Variables:

λ_t^D	Day-ahead market price in a time period t.
λ_t^r	Real-time price in a time period t.
W_t^{ac}	Actual wind power production in a time period t.
ρ_o	Ratio between the real-time and day-ahead prices.

Other Variables:

VaR_α	Value at risk at α confidential interval.
CVaR_α	Conditional value at risk at α confidential interval.
π_T	Expected profit of a conventional power producer.
π_W	Expected profit of a wind power producer.
Δ_t	Total deviation of energy incurred by a wind producer with respect to the schedule in a time period t.
Δ_t^+	Positive deviation of wind energy.
Δ_t^-	Negative deviation of wind energy.

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

Constants and Parameters:

c^{cap}	Energy price cap.
d_t	Duration of a time period t.
pr_ω	Probability of occurrence of a scenario ω.
$P_g^{\min}$	Minimum power output of a conventional unit g.
$P_g^{\max}$	Minimum power output of a conventional unit g.
RU_g	Ramp-up rate for a conventional unit g.
RD_g	Ramp-down rate for a conventional unit g.
a_g, b_g, c_g	Thermal heat rate curve parameters.
StUP_g	Start-up cost for a conventional unit g.
u_{gIC}	Initial start of a conventional unit g.

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$W^{\max}$	Installed capacity of a wind producer.
α	Per-unit confidence level.
β_T	Risk-aversion parameter of conventional power producers.
β_W	Risk-aversion parameter of wind producers.

I. Introduction

THE installed capacity of wind power is increasing rapidly all around the world. The global installed wind capacity reached 237 GW at the end of 2011 [1]. The United States, Germany, Spain, and China are the leading countries in terms of installed wind capacity. China saw the largest additions of new capacity in 2011. According to recent reports [1], [2], the total installed wind capacity in the U.S. reached over 46 GW with nearly 5.6 GW of newly installed wind capacity in 2011. Due to the uncertainty and intermittency of wind power, the increasing penetration of wind power into electric power systems will pose challenges to power system operators.

In the United States, around 66% of the installed wind power was sold through power purchasing agreements (PPAs) at a fixed price in 2011 [3]. However, since the PPA price continuously declines after reaching the peak at 2008 and the availability of PPA contracts has been limited since 2010, wind power producers can no longer obtain stable revenues through PPAs. Some of the U.S. and European wind power producers have committed themselves in a similar way as other market participants in energy markets and are subjected to monetary penalties if they deviate from their commitment [3]–[6]. For example, the Midwest Independent System Operator (MISO), ERCOT, and New York ISO (NYISO) all allow wind resources to bid in the day-ahead market. The wind curtailment management has been treated in the same way as other conventional generators in most ISOs or RTOs [4]. For example, in the MISO's market, wind and conventional generators will be curtailed out of the market for transmission congestion and minimum generation events. The order of the curtailment is determined based on generators' impacts on the transmission constraints and priority of transmission service. In this paper, wind power producers are treated in the same way as conventional generators in the day-ahead and real-time markets; ISOs cannot curtail wind power on an involuntary basis.

The uncertainty in wind power generation is a major obstacle to the natural incorporation of wind producers into a competitive market framework from both technical and economic perspectives. The question of how wind producers can benefit from a competitive environment has been raised recently and several solutions have been proposed. One solution is based on a combined and coordinated use of wind power and energy storage technologies [7]–[10], e.g., pumped-hydro storage, compressed air, etc. However, the availability of utility-scale storage is still limited. Another solution is using financial options as a tool for wind producers to hedge against generation uncertainty [11]. Some papers have also presented using stochastic models to generate optimal bidding strategies for wind power producers participating in the day-ahead or adjustment market [12]–[14]. In [15], different offering strategies for wind producers were evaluated and the results showed that the use of stochastic models to generate offering strategies outperformed those generated by using forecasted values of wind power directly. The reserve market has also been included in some models to maximize the revenue of wind producers. Liang *et al.* [16] proposed a model for wind producers to participate in both energy and regulation markets to increase revenue and system security. Coordinated trading of wind and thermal energy produced by the same producer was studied in [17], where a two-stage stochastic optimization model was proposed to maximize the total profit from both wind power plants and thermal generators which have high production costs and fast-ramping, near-zero minimum output power. By transferring the risk from wind power plants to thermal generators of the producer, the risk associated with wind uncertainty is mitigated.

The existing work considered only the behavior of wind power producers. However, as participants in the electricity market, wind power producers will compete with other conventional power producers. Each market participant bids with the target of maximizing their own profit. The bidding strategy of each participant will definitely influence the clearing process of both energy and reserve markets.

This paper proposes a model that uses stochastic programming to generate optimal bidding strategies to maximize the profits of wind and conventional power producers from both the energy market and a new bilateral reserve market. In the proposed model, a new trading mechanism is introduced in which wind producers are allowed to buy energy from the bilateral reserve market to minimize the risk of losing money due to their production uncertainties; the energy offers and bids in the new bilateral reserve market as well as the reserve price are settled among wind and conventional power producers by using game theory. Case studies for games with different types and numbers of wind and conventional power producers are provided to demonstrate the effectiveness of the proposed model.

II. Problem Formulation Methodologies

A. Market Framework and Assumptions

Consider a pool-based electricity market in which suppliers, including wind power producers, submit energy offer curves into day-ahead energy and reserve markets for each hour of the next operating day. The time frames for market clearance are illustrated in Fig. 1. In most U.S. markets, the day-ahead energy and reserve markets are cooptimized by using a single clearing process determined by the market operators, from which the energy and reserve transactions coming into effect during each hour of the next operating day are cleared at a given time of the current operating day. Once the markets are cleared, the location marginal price (LMP), the reserve market clearing price, and the cleared energy volume of each participant are settled. Some American markets, e.g., the PJM Interconnection market, allow generating resources to rebid if they are not selected in the day-ahead market. This rebidding is not considered in this paper. For wind power producers, some American markets, e.g., the California Independent System Operator (CAISO) market, allow them to reschedule their output around one hour ahead (defined as 75 minutes ahead). These specific cases are not discussed in this paper. Finally, the real-time market is carried

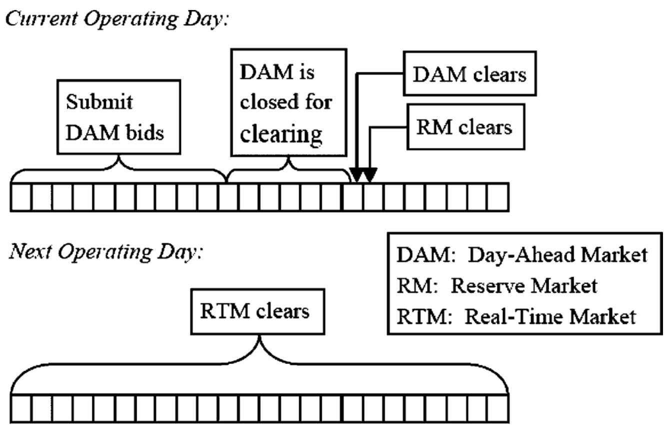

Fig. 1. Time frames for clearing in an electricity market.

out just minutes before the actual power delivery by producers to ensure a real-time balance between generation and demand. This is done by offsetting the difference between the real-time operation and the corresponding energy program settled in the day-ahead market [18]. A real-time price is calculated for the real-time market based on real-time operating conditions. For each hour, producers are paid for the cleared energy volume at the day-ahead LMP. While in the real-time market, producers are paid at the real-time price for positive energy deviations (i.e., the production in the real-time market is higher than that scheduled in the day-ahead market) and will pay for negative energy deviations (i.e., the production in the real-time market is lower than that scheduled in the day-ahead market). Moreover, the participants who offer reserve are paid for the cleared reserve volume at the reserve price, while the participants who buy reserve are charged for the cleared reserve volume at the reserve price.

Several assumptions are made to simplify the problem formulation. 1) The participants in the electricity market are wind and conventional power producers. The wind power producers predict their maximum possible power outputs with errors. The conventional power producers can control their power outputs precisely and failures of facilities are not considered in operation. 2) Wind and other power producers have no market-power capability in energy markets, which include the day-ahead and real-time markets. Therefore, the proposed model cannot be applied to power producers whose bidding strategies have significant impact on the market clearing price. 3) The introduced bilateral reserve market is mixed with the system-wide reserve to provide standby power to cover the intermittency and uncertainty of nondispatchable sources, which are wind power in this paper. The bilateral reserve is provided by conventional power producers and consumed by wind power producers. 4) The bilateral reserve settlement among wind and conventional power producers can be seen as a new trading mechanism for the new type of reserve adding to the existing system-wide reserve. The bilateral reserve settlement price and volumes of specific providers are cleared among the wind power producers and the conventional power producers who provide this new type of reserve. This new bilateral trading mechanism does not change current implementation of the system-wide reserve, regulation, and other auxiliary services for mitigating other uncertainties (e.g., large load uncertainties) in the system.

B. Two-Stage Stochastic Optimization Approach

For wind power producers, the uncertainties in obtaining the maximum profit from both energy and bilateral reserve markets include wind power output, hourly LMP, real-time price, and bilateral reserve market clearing price. The problem of maximizing the total profit of a wind power producer can be formulated using constrained mixed-integer stochastic programming, where the uncertainties in optimization are handled through a two-stage decision-making process. The decisions in the first stage are here-and-now decisions, which are made before the realization of the stochastic process. The decisions in the second stage are wait-and-see decisions, which are affected by those in the first stage. If the stochastic process is represented by a set of possible scenarios, second-stage decision variables are then defined for each single scenario considered [18].

In this study, the stochastic process for a wind power producer involves the following:

1) Design the offer strategy for the day-ahead energy and bilateral reserve markets and submit the resulting energy selling offers and reserve bidding offers to the market operator for each period of the market horizon. In this stage, decisions are made based on a plausible realization of the stochastic process, namely, the day-ahead and real-time energy prices and wind power production. The bilateral reserve price is determined by using game theory, which is described in Section II-C.

2) The second-stage decisions are made for a given realized scenario, where the day-ahead market price, the real-time price, and the wind energy produced become known. Therefore, the payment or cost of wind power producers in the real-time market can be calculated.

The approach for conventional power producers is similar to that for wind power producers. The only difference is that the production of a conventional power producer can be controlled and, therefore, is not considered as a stochastic process.

C. Auction Games and Nash Equilibrium

A game is a "formal representation of a situation in which a number of individuals interact in a setting of strategic independence [19]." There are four elements in a game [20]: 1) the players, 2) the rules of the game, 3) the outcomes, and 4) the payoff and preference (utility functions) of the players. A game can be either cooperative, where the players collaborate to achieve a common goal, or noncooperative, where they act on their own.

In this paper, different energy suppliers are the game players. Each player has the historical information of other players' past actions. A strategy is a rule that tells the players which action(s) they should take. Assuming that the players are noncooperative, know the payoff functions of other players, and try to maximize their payoff functions while considering their rivals' bidding strategies, the Nash Equilibrium [19] will occur when no player will have the incentive to change its offering/bidding strategy.

In order to benefit from participating in the bilateral reserve market, wind producers will not buy reserve from the bilateral reserve market if the reserve clearing price exceeds the real-

time price while the conventional power producers will not offer reserve in the bilateral reserve market if the real-time price is lower than the day-ahead price. This means that the offer price for reserve at a certain time t can take any value between the day-ahead price λ_t^D and the higher value between the real-time price λ_t^r and the energy price cap c^{cap} specified by the market operator

$$\lambda_t^D \leq \lambda_t^R \leq \max(\lambda_t^r,\ c^{\mathrm{cap}}). \tag{1}$$

A wind power producer can bid reserve energy provided by conventional power producers at any value between zero and the predicted imbalance power during the market operation

$$0 \leq W_t^R \leq \Delta_t^-. \tag{2}$$

Also, a conventional power producer can offer reserve energy of its unit g to a wind power producer at any value between zero and the maximum power output of this unit

$$0 \leq P_{gt}^R \leq P_g^{\max}. \tag{3}$$

Let γ_i denote player i's strategy and γ_{-i}^* denote other players' strategies. Player i's total profit is π_i, which includes the revenue from both energy and bilateral reserve markets and can be obtained by solving a two-stage stochastic programming problem described in Section III.

Let Γ_i be the set of continuous strategies of player i. For a continuous game, a strategy tuple $\{\gamma_i^*\}_{i=1\ to\ I}$ is a Nash Equilibrium if the following equilibrium condition is satisfied [20] for all continuous strategies γ_is, where $i = 1, \ldots, I$:

$$\pi_i(\gamma_i^*, \gamma_{-i}^*) \geq \pi_i(\gamma_i, \gamma_{-i}^*), \quad \forall \gamma_i \in \Gamma_i,\ \forall i. \tag{4}$$

The continuous equilibriums are difficult to obtain because the payoff function π has no explicit formula. To simplify the solution process, the continuous strategy set of player i, Γ_i, is appropriately discretized into N_i choices; then the set of the resulting discrete strategies of player i can be written as $\Omega_i = \{\gamma_{i,n}, n = 1, \ldots, N_i\}$. Since a player i has N_G generating units and each unit can have N_{ig} discrete strategies, N_i can be expressed as $N_i = \prod_{g=1}^{N_G} N_{ig}$. Moreover, since there are totally I players, a game can then be formed with a total number of $N = \prod_{i=1}^{I} \prod_{g=1}^{N_G} N_{ig}$ strategy tuples. The Nash solution can then be searched among the N strategy tuples. Similar to (4), $\{\gamma_i^*\}_{i=1\ \mathrm{to}\ I}$ is a Nash Equilibrium for the matrix game if the following discrete equilibrium condition is satisfied:

$$\pi_i(\gamma_i^*, \gamma_{-i}^*) \geq \pi_i(\gamma_{i,n}, \gamma_{-i}^*), \quad \forall \gamma_{i,n} \in \Omega_i,\ \forall i. \tag{5}$$

III. Mathematical Formulation

A. Scenario Generation and Reduction

In stochastic programming, stochastic processes can be represented using continuous or discrete random variables. In the best case, stochastic programming problems with continuous random variables can only be solved in small or illustrative instances [18]. For this reason, scenario representation of random variables becomes indispensable in solving stochastic problems. The set of values used to model a random variable is usually arranged in a so-called scenario tree, as illustrated in Fig. 2. A scenario tree comprises a set of nodes and arcs. The node in the first stage is called the root node. The nodes in the last stage are called leaves. A scenario is a path from the root to the leaf. A stage is a moment in the time line when the decisions are taken.

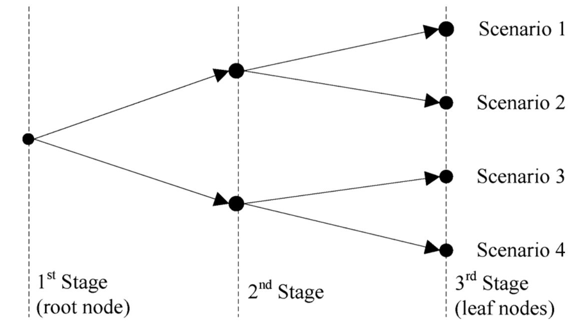

Fig. 2. Typical scenario tree.

Different techniques have been proposed in the literature to build scenario trees. Given that the computational burden of a stochastic programming problem increases rapidly with the number of scenarios, a mathematical tool aimed at scenario reduction becomes necessary. In this paper, a procedure combining a path-based method [13] and a scenario reduction technique [21] is used to generate a two-stage scenario trees. A seasonal autoregressive integrated moving average (ARIMA) model [13] is used to generate a large number of scenarios of wind power, day-ahead price, and real-time price predictions. Then, a fast-forward scenario-reduction algorithm [21] is used to obtain a reduced scenario set with a sufficiently small number of scenarios from an iterative process. In each iteration, the scenario that minimized the Kantorovich distance between the reduced set and the original set is selected from the set of unselected scenarios and included in the reduced set. The algorithm stops if either the required number of scenarios or a certain Kantorovich distance is attained.

B. Mechanism for Real-Time Prices

As described in Section II-A, the real-time market, i.e., the balancing market, deals with the difference between the energy produced during the real-time operation and the energy scheduled in the day-ahead market. In some U.S. electricity markets, e.g., the PJM market, the actual quantity deviation from the scheduled hourly quantity in the day-ahead market is priced in the real-time market. Define $\rho_o = \lambda^r/\lambda^D$ to be the ratio between the real-time and day-ahead prices. The mechanism for real-time prices can be explained as follows:

1) If a player's day-ahead scheduled power is less than the actual power that can be generated in the real-time market and the real-time price excesses the day-ahead price, which means $\rho_o \geq 1$, this player will have incentive to sell extra power into the real-time market and will be paid at the real-time price for the extra power.

2) If a player's day-ahead scheduled power is greater than the actual power generated in the real-time market, which means $\rho_o < 1$, this player will have to pay for the deviation power at the real-time price.

3) When the power system's demand is deficit, $\rho_o \geq 1$; otherwise, when the power system's generation is more than demand, $\rho_o < 1$.

C. Conventional Power Producers

The conventional power producers, such as thermal and hydro power plants, can control their power outputs if no generator failure is considered. The problem of obtaining the best bidding strategy for conventional power producers is formulated as a two-stage stochastic program to maximize the profit of a thermal power producer is

$$\begin{aligned}\underset{P^D_{gt\omega},P^r_{gt\omega},\varsigma,\eta_\omega,u_{gt}}{\text{Maximize}} \quad \pi_T = &\sum_{\omega=1}^{N_\Omega} pr_\omega \sum_{t=1}^{N_T}\sum_{g=1}^{N_G} d_t \\ &\times \left[\lambda^D_{t\omega}P^D_{gt\omega}+\lambda^r_{t\omega}P^r_{gt\omega}+\lambda^R_t P^R_{gt}\right. \\ &\quad -C_g\left(P^D_{gt\omega}+P^r_{gt\omega}+P^R_{gt}\right) \\ &\quad \left.-\max\left(0,\mathrm{StUP}_{gt}(u_{gt}-u_{g(t-1)})\right)\right] \\ &+\beta_T\left[\zeta-\frac{1}{1-\alpha}\sum_{\omega=1}^{N_\Omega} pr_\omega\eta_\omega\right] \end{aligned} \tag{6}$$

Subject to :

$$u_{gt}P_g^{\min} \leq P^D_{gt\omega}+P^r_{gt\omega} + P^R_{gt} \leq u_{gt}P_g^{\max}, \quad \forall t,\omega,g \tag{7}$$

$$u_{gt}P_g^{\min} \leq P^D_{gt\omega} \leq u_{gt}P_g^{\max}, \quad \forall t,\omega,g \tag{8}$$

$$u_{gt}P_g^{\min} \leq P^r_{gt\omega} \leq u_{gt}P_g^{\max}, \quad \forall t,\omega,g \tag{9}$$

$$P^{ac}_{gt\omega} = P^D_{gt\omega}+P^r_{gt\omega}+P^R_{gt}, \quad \forall t,\omega,g \tag{10}$$

$$P^{ac}_{gt\omega}-P^{ac}_{g(t-1)\omega} \leq \mathrm{RU}_g, \quad \forall t,\omega,g \tag{11}$$

$$P^{ac}_{g(t-1)\omega}-P^{ac}_{gt\omega} \leq \mathrm{RD}_g, \quad \forall t,\omega,g \tag{12}$$

$$C_g(P) = a_g + b_gP + c_gP^2 \tag{13}$$

$$\left(\lambda^D_{t\omega}-\lambda^D_{t\omega'}\right)\left(P^D_{gt\omega}-P^D_{gt\omega'}\right) \geq 0, \quad \forall t,\omega,\omega',g \tag{14}$$

$$P^D_{gt\omega} = P^D_{gt\omega'}, \quad \forall t,\omega,\omega',g : \lambda^D_{t\omega} = \lambda^D_{t\omega'} \tag{15}$$

$$\eta_\omega \geq 0, \quad \forall\omega \tag{16}$$

$$\begin{aligned}\zeta - \sum_{t=1}^{N_T}\sum_{g=1}^{N_G}&\left[\lambda^D_{t\omega}P^D_{gt\omega}\right. \\ &+\lambda^r_{g\omega}P^r_{gt\omega}+\lambda^R_tP^R_{gt} \\ &-C_g\left(P^D_{gt\omega}+P^r_{gt\omega}+P^R_{gt}\right) \\ &\left.-\max\left(0,\mathrm{StUP}_{gt}(u_{gt}-u_{g,t-1})\right)\right] \leq \eta_\omega, \quad \forall\omega \end{aligned} \tag{17}$$

where the objective function (6) comprises two terms: 1) the expected profit, which equals the revenues from the day-ahead, real-time, and bilateral reserve markets minus the production cost and start-up cost; and 2) the CVaR multiplied by a weighting factor β_T, which allows controlling the risk-aversion degree of the conventional power producer [22].

In this model, the first-stage decision variable is the hourly bid of the energy volume $P^D_{gt\omega}$ of the thermal units while the second-stage decision variable is the real-time output $P^r_{gt\omega}$ of the thermal units. Constraints (7)–(9) bound the maximum power capacity of each thermal unit. The actual total power generated by each thermal unit is expressed in Constraint (10). Constraints (11) and (12) represent the ramp-up and ramp-down limits of each thermal unit, respectively. The production cost C_g of each thermal unit is expressed as a quadratic constraint (13). Constraint (14) enforces a nondecreasing offer curve. Constraint (15) constitutes the nonanticipativity conditions related to the decisions made in first stage. Constraints (16) and (17) are used to compute CVaR.

Risk control is an important issue when formulating a stochastic programming model. VaR has been used to quantify a portfolio exposure to risk [23]. VaR_α is the VaR at a certain confidence level α and equals to the largest value of ζ ensuring that the probability of obtaining a profit less than ζ is lower than $1-\alpha$. In this work, the VaR_α is the upper bound of the profit for the $(1-\alpha)\times 100\%$ least profitable scenarios [17]. A serious shortcoming of using VaR is that it does not reflect any information about the profits of the scenarios beyond the value of VaR. Moreover, it is difficult to handle VaR when the profits are not normally distributed [22].

CVaR, which has been proven to have better performance than VaR [22], is used in this work as a risk measurement. CVaR_α is computed as the expected value of the profit associated with the $(1-\alpha)\times 100\%$ worst scenarios. The value of α in (6) is usually chosen to be around 0.95 [15], [17], [18]. The weighting parameter β_T is set by the producers to indicate their degree of willingness to take risks. A higher value of β_T indicates that the producers are more risk averse, which results in a higher value of CVaR and a lower value of the expected profit. Therefore, the value of β_T is chosen as a tradeoff between expected profit and risk.

The model to maximize the profit of a hydro power producer is similar to that of the thermal power producer, except that the fuel cost is set to be zero and the ramp-up and ramp-down constraints (11) and (12) are ignored.

D. Wind Power Producers

The model to maximize the profit of a wind producer is

$$\begin{aligned}\underset{W^D_{t\omega},\,\varsigma,\,\eta_\omega}{\text{Maximize}} \quad \pi_W = &\sum_{\omega=1}^{N_\Omega} pr_\omega \sum_{t=1}^{N_T} \\ &\times\left[\lambda^D_{t\omega}W^D_{t\omega}d_t\right. \\ &\quad \left.+\lambda^r_{t\omega}\Delta^+_{t\omega}-\lambda^r_{t\omega}\Delta^-_{t\omega}-\lambda^R_tW^R_td_t\right] \\ &+\beta_W\left[\zeta-\frac{1}{1-\alpha}\sum_{\omega=1}^{N_\Omega} pr_\omega\eta_\omega\right]\end{aligned} \tag{18}$$

Subject to :

$$0 \leq W^D_{t\omega} \leq W^{\max}, \quad \forall t,\omega \tag{19}$$

$$\Delta^+_{t\omega}-\Delta^-_{t\omega} = \Delta_{t\omega}, \quad \forall t,\omega \tag{20}$$

$$\Delta_{t\omega} = d_t\left(W^{ac}_{t\omega}+W^R_t-W^D_{t\omega}\right), \quad \forall t,\omega \tag{21}$$

$$0 \leq \Delta^+_{t\omega} \leq \left(W^{ac}_{t\omega}+W^R_t\right)d_t, \quad \forall t,\omega \tag{22}$$

$$0 \leq \Delta^{-}_{t\omega} \leq W^{D}_{t\omega} d_t, \quad \forall t, \omega \tag{23}$$

$$W^{D}_{t\omega} = W^{D}_{t\omega'}, \forall t, \omega, \omega' : \lambda^{D}_{t\omega} = \lambda^{D}_{t\omega'} \tag{24}$$

$$\left(\lambda^{D}_{t\omega} - \lambda^{D}_{t\omega'}\right)\left(W^{D}_{t\omega} - W^{D}_{t\omega'}\right) \geq 0, \quad \forall t, \omega, \omega' \tag{25}$$

$$\eta_\omega \geq 0, \quad \forall \omega \tag{26}$$

$$\zeta - \sum_{\omega=1}^{N_\Omega} pr_\omega \sum_{t=1}^{N_T} \left[\lambda^{D}_{t\omega} W^{D}_{t\omega} d_t + \lambda^{r+}_{t\omega} \Delta^{+}_{t\omega} - \lambda^{r-}_{t\omega} \Delta^{-}_{t\omega} - \lambda^{R}_{t} W^{R}_{t} d_t\right] \leq \eta_\omega, \quad \forall \omega \tag{27}$$

where the objective function also comprises two terms: 1) the expected profit, which equals the revenue from the day-ahead market plus the revenue from positive energy deviations in the real-time market minus the cost for negative energy deviations in the real-time market and the cost in the bilateral reserve market; and 2) the CVaR multiplied by a weighting factor β_W, which controls the risk-aversion degree of the wind producer.

Again in this model, the first-stage decision variable is the hourly bid of the energy volume $W^{D}_{t\omega}$ of the wind producer while the second-stage variables are the real-time energy deviations $\Delta^{+}_{t\omega}$ and $\Delta^{-}_{t\omega}$ of the wind producer. Constraint (19) limits the amount of wind energy that can be traded in the day-ahead market. Constraints (20)–(23) determine the total positive and negative energy deviations incurred by the wind producer per period and scenario. Constraint (24) constitutes the nonanticipativity conditions related to the decisions made in first stage. Constraint (25) enforces a nondecreasing offer curve. Constraints (26) and (27) are used to compute CVaR.

The two models of conventional and wind power producers are connected through the reserve volumes P^{R}_{gt} and W^{R}_{t} and the reserve clearing price λ^{R}_{t} in the bilateral reserve market. The total reserve volume (i.e., the sum of reserve volumes P^{R}_{gt}) of conventional power producers should be equal to W^{R}_{t}.

E. Solving Matrix Games

The discretization of the strategy variables γ_is may cause loss or artificial creation of Nash Equilibrium as discussed in [20]. To capture a possibly missing Nash solution, the standard discrete equilibrium condition (5) is loosened by ε to yield an approximate Nash Equilibrium

$$\pi_i(\gamma^*_i, \gamma^*_{-i}) \geq \pi_i(\gamma_i, \gamma^*_{-i}) - \varepsilon, \quad \forall \gamma_{i,n} \in \Omega_i, \forall i. \tag{28}$$

The matrix payoffs are suppliers' profits from both energy and bilateral reserve markets. These profits are obtained by solving the two-stage constrained stochastic programming problems described in Sections III-C and III-D for all strategy tuples in the increasing order of bidding price and energy. After the payoffs for each strategy tuple are obtained, the strategy tuples are examined for the Nash Equilibrium condition (28). Reference [20] presented a method to find an appropriate value of ε for determining an approximate Nash Equilibrium.

The complete solution process for trading wind power in both energy and bilateral reserve markets is depicted in a flowchart in Fig. 3, which consists of two parts: obtaining the matrix payoffs by stochastic programming on the left-hand side and solving for the Nash Equilibrium on the right-hand side. In this paper, strategies are generated for each wind power producer and each unit of conventional power producers. The strategies contain two variables: the reserve energy volume P^{R}_{gt} or W^{R}_{t} that a conventional generating unit would like to offer or a wind producer would like to buy, respectively, and the reserve clearing price λ^{R}_{t} settled among conventional and wind power producers. These variables are discreated separately into a limited number of values within their limits defined by (1)–(3). A strategy tuple is then created by combining a value of these variables of all the players in the game. For each strategy tuple, the stochastic optimization models (6)–(17) and (18)–(27) are executed for conventional and wind power producers, respectively, during which P^{R}_{gt} (or W^{R}_{t}) and λ^{R}_{t} are constant values in this strategy tuple. Then the Nash Equilibrium condition is examined for each solved strategy tuple to determine which strategy tuple yields the maximum profits for both conventional and wind power producers. Finally, the stochastic programming is executed for the best strategy tuple (i.e., the Nash Equilibrium) to obtain the optimal bidding curve. The parameter $\varepsilon_{\max}$ is relatively small compared to the expected profit obtained from the stochastic models, e.g., 1% of the expected profit. If no solution is obtained from the search for the Nash Equilibrium, wind producers will not bid reserve and conventional power producers will not offer reserve in the new bilateral reserve market.

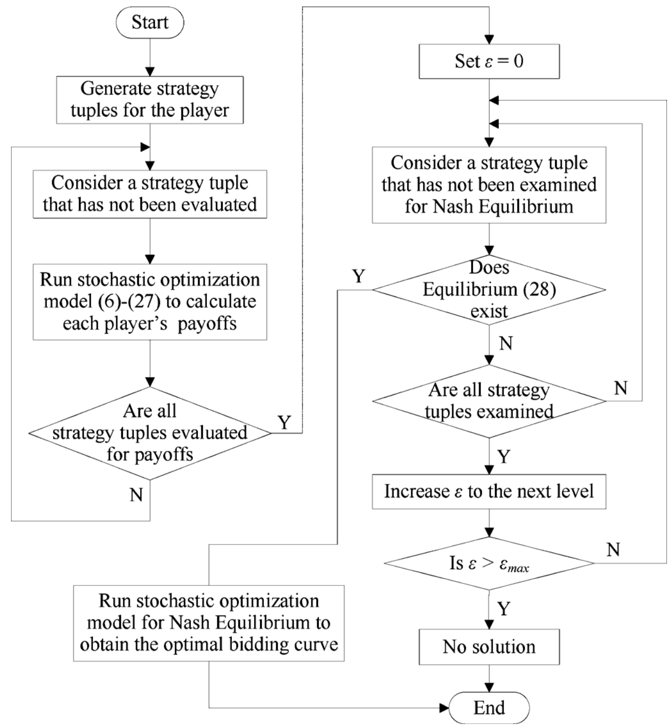

Fig. 3. Flowchart for trading wind power using the proposed model.

Compare to the work of [17], in this paper the trading between wind and thermal energy is not regulated by the owners but by profit. The trading will happen only if the transaction is beneficial to both producers. The profits of different producers are maximized separately. Moreover, game theory is applied in this paper to determine the reserve trading volume and price between conventional and wind power producers.

TABLE I
THERMAL UNIT DATA

Unit Number	1	2	3
$P^{\min}$ (MW)	0	5	5
$P^{\max}$ (MW)	50	45	45
RU (MW/Hr)	50	15	15
RD (MW/Hr)	50	15	15
u_{IC} (Hrs)	0	0	0
StUp ($)	0	88	88
Fuel Type	Gas	Gas	Gas
a	0	85.509	82.342
b	80	70.85831	68.23393
c	0	0.18819	0.18122

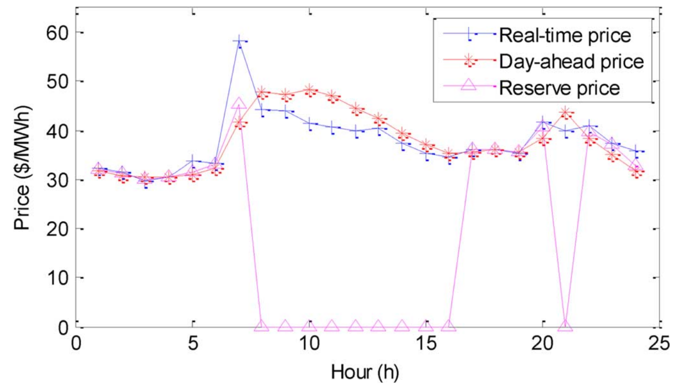

Fig. 4. Case 1: real-time, day-ahead, and settled reserve prices.

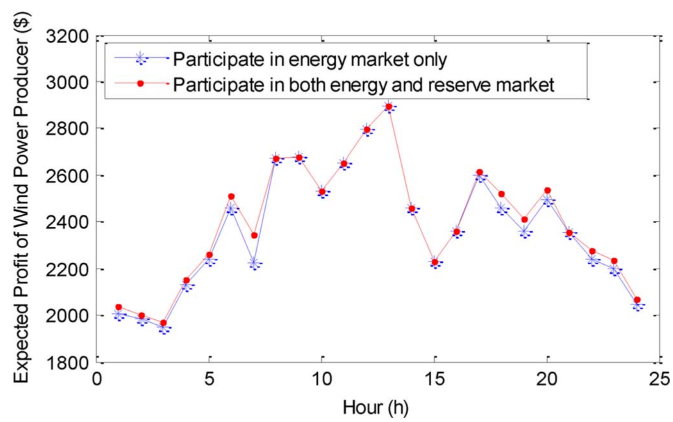

Fig. 5. Case 1: expected profits of the wind power producer.

IV. CASE STUDY

Case studies for games with different numbers of players are carried out to demonstrate the effectiveness of the proposed model. In each case the proposed model is compared with the traditional model which does not have the market for trading the new type of reserve. Therefore, the traditional model is obtained by setting the reserve price as well as the offering and bidding reserve capacities to zero in the objective functions (6) and (18). In the traditional model, there are no transactions between wind power producers and conventional power producers in the bilateral reserve market and, therefore, no game theory is used. All of the cases are simulated using CPLEX 12.1 in GAMS [24]. The computer used for simulation studies has a 3.16-GHz, 4-core CPU and a 16-GB RAM.

A. Two-Player Game

Consider a game with two players: one thermal power plant with three units and one wind power plant. The installed capacities of the wind and thermal power plants are 100 and 140 MW, respectively. Since there is only one thermal power producer in the market of providing the new type of bilateral reserve, the wind producer decides how much reserve it would like to buy from the thermal power producer and at what price, while the thermal power producer decides the price of the reserved power and how much reserve it would like to sell. The thermal units' operating characteristics are given in Table I. The reserve price bid cap c^{cap} is \$1000/MWh in the reserve market. The ARIMA model is used to generate 5000 scenarios for wind power, day-ahead price, and real-time price predictions, respectively. Scenario reduction is then performed to reduce the scenarios of wind power, day-ahead price, and real-time price predictions to 5 each. Therefore, the final reduced scenario tree has 125 scenarios. The wind plant data is obtained from the National Renewable Energy Laboratory website [25]. The energy prices, including both the day-ahead price and real-time price, are obtained from the PJM website [26]. The risk-aversion parameter is $\beta_T = \beta_W = 0.5$. The confidence level is $\alpha = 0.95$. The maximum approximation parameter $\varepsilon_{\max}$ (see Fig. 3) is \$10. For each thermal unit, three discrete reserve power volumes and three reserve clearing prices are generated. Assume that the reserve clearing price strategies are identical for the three units. Totally 81 strategy tuples are generated in this case study. The bidding curve for the wind producer is generated by solving the two-stage stochastic optimization problem (6)–(27), where the wind generation, real-time price, and day-ahead price are obtained through forecasting and scenario generation and reduction, while the reserve price settled between wind and conventional power producers is obtained by using the game theory. The expected profit is then calculated by applying the bidding curve obtained into the electricity market using real data obtained from the PJM market.

1) Case 1: Real-Time Price Is Lower Than Day-Ahead Price: A day is selected in which the real-time price has a low standard deviation, and during some hours the real-time price is lower than the day-ahead price. The real-time and day-ahead prices obtained from the PJM market and the reserve price settled between wind and conventional power producers obtained from the proposed model are shown in Fig. 4. The total expected profits of the wind producer to gain from participating in the energy market only and from participating in both the energy and bilateral reserve markets are shown in Fig. 5. The increased profit of the wind producer from playing a game with the thermal power producer in the bilateral reserve market to buy reserve energy is shown in Fig. 6. The energy market bidding curves of the wind producer participating in the energy market only and in both the energy and bilateral reserve markets for the 7th and 24th hours are shown in Fig. 7.

In this case, when the real-time price is lower than the day-ahead price, the thermal units would rather sell power in the day-ahead market than the bilateral reserve market. The reserve price is then set to zero since there is no transaction of reserve in the bilateral reserve market. During hours when the real-time price is higher than the day-ahead price, the reserve price is

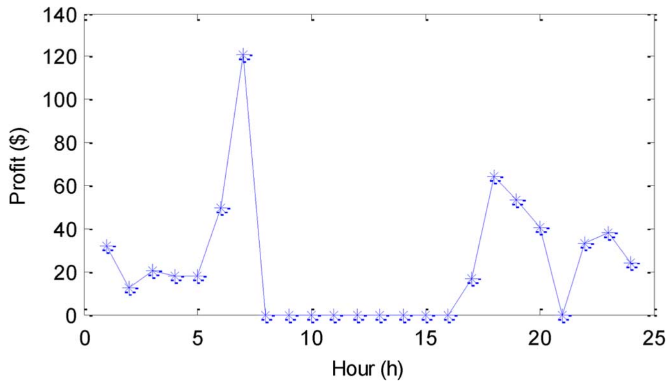

Fig. 6. Case 1: increased profit of the wind power producer from participating in both the energy and bilateral reserve markets.

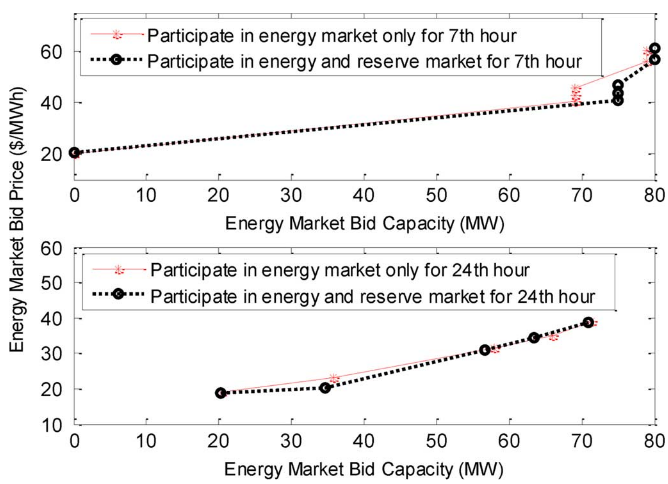

Fig. 7. Case 1: energy market bidding curves of the wind producer generated for the 7th and 24th hour.

settled between the real-time price and day-ahead price. Thus, the wind producer could buy cheaper energy from the bilateral reserve market to gain a higher profit, as shown in Figs. 5 and 6. Buying energy from the bilateral reserve market has changed the wind bidding curve, as illustrated in Fig. 7. Compared to the case that the wind producer only participates in the energy market, if the wind producer participates in both the energy and bilateral reserve markets, it will bid at a higher price for low capacities and then decline its price to bid at a lower price for high capacities in the energy market. Moreover, the maximum capacity and price that the wind producer wishes to bid in the energy market are higher than those if it only participates in the energy market. These observations are expected as the wind producer tends to first bid a higher price to cover the cost it will spend to buy reserve power and then to make more profit by selling more power.

2) Case 2: Real-Time Price Has a High Mean Value and Standard Deviation: In this case, a day is chosen in which the mean value and standard deviation of the real-time price is high. This means that the real-time price is more difficult to predict for market participants. The real-time price, day-ahead price, and settled reserve price are shown in Fig. 8. The total expected profits of the wind producer to gain from participating in the energy market and from participating in both the energy and bilateral reserve markets are shown in Fig. 9. The increased profit of the wind producer from buying reserve energy is shown in

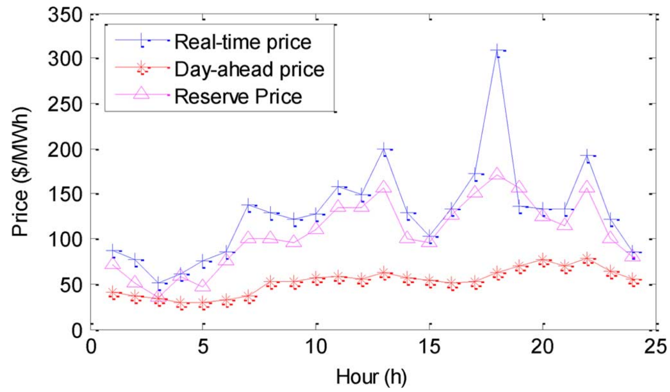

Fig. 8. Case 2: real-time, day-ahead, and settled reserve prices.

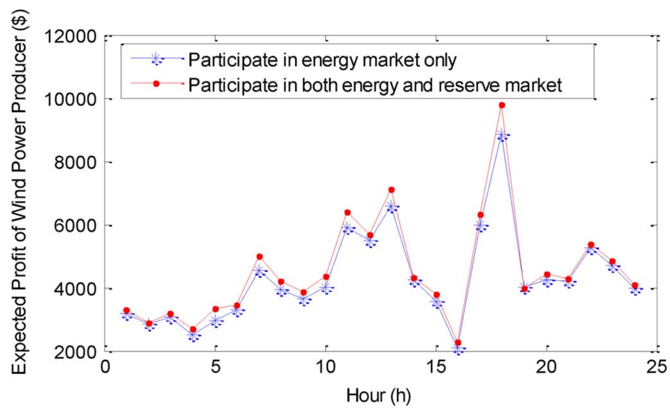

Fig. 9. Case 2: expected profits of the wind power producer.

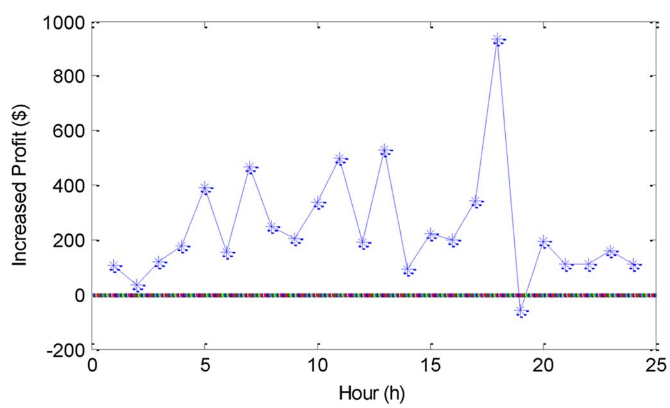

Fig. 10. Case 2: increase profit of the wind power producer from participating in both energy and bilateral reserve markets.

Fig. 10. The energy market bidding curves of the wind producer in participating in the energy market only and in both the energy and bilateral reserve markets for the 18th and 19th hour are shown in Fig. 11.

In this case, playing a game in the bilateral reserve market to buy reserve energy will not always benefit the wind power producer. In Fig. 8, the reserve price in the 19th hour is even higher than the real-time price. Due to an inaccurate forecasting of the real-time price, the wind producer buys expensive power from the bilateral reserve market, which results in a lower (negative) expected profit in that hour compared to the case that the wind producer does not participate in the bilateral reserve market, as shown in Fig. 10. However, during most times the wind producer gains more profit from playing the game in the bilateral

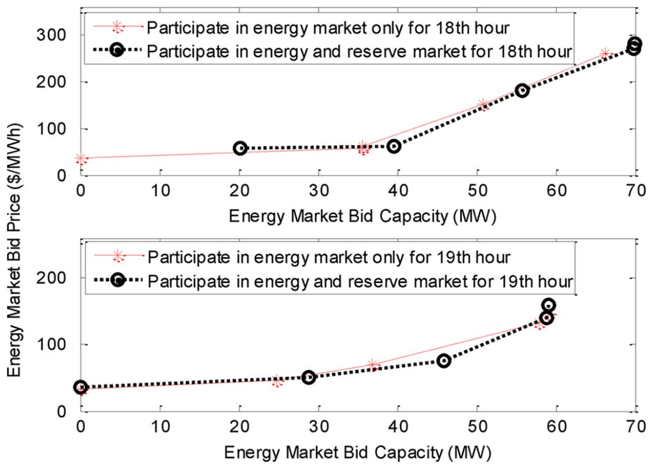

Fig. 11. Case 2: energy market bidding curves of the wind producer generated for the 18th and 19th hour.

reserve market. The bidding curves in the 18th and 19th hour in Fig. 11 show the same features as in Fig. 7.

The mean values of the increased profit of the wind power producer by playing the game in the bilateral reserve market are $22.5 in Case 1 and $244.8 in Case 2. A higher real-time price results in more profit increase. The reserve price also has a tight correlation with the real-time price and depends more on the fluctuations of the real-time price. A highly fluctuated real-time price is more difficult to predict, which increases the risk of losing money for the wind producer in the joint energy and bilateral reserve markets.

B. Case 3: A Multiplayer Game With Multiple Types of Conventional Power Producers

Based on the two-player game, a multiplayer game is considered with an additional hydro power producer. The hydro power producer has three hydro units with a total capacity of 200 MW. As in Cases 1 and 2, the total number of scenarios in this case study is reduced to 125. However, the number of strategy tuples increases to 81^2. Obviously, the computational time increases with the number of players. Effective strategy tuple reduction can be used to reduce the computational time. For example, the number of strategy tuples can be significantly reduced by only generating strategies for each player instead of for each unit. Then the total number of strategy tuples for this case is only 81. In a practical electricity market with many players, only those with fast-ramping output power capability are likely to provide reserve for wind producers and, therefore, need to be considered in the game. Moreover, since each strategy tuple can be examined separately, the proposed model and solution process can be implemented easily and efficiently using parallel computing techniques. This, combined with efficient scenario and strategy tuple reduction and player selection, will make the proposed model applicable to practical electricity markets with many players.

The hydro units' characteristics are given in Table II. It is assumed that the hydro units have sufficient source from the reservoir to generate electricity. The real-time, day-ahead, and settled reserve prices are shown in Fig. 12. The total expected profits of the wind producer to gain from participating in the

TABLE II
HYDRO UNIT DATA

Unit Number	1	2	3
P^{min} (MW)	0	5	5
P^{max} (MW)	45	75	80
StUp($)	60	100	150
Fuel Type	Hydro	Hydro	Hydro

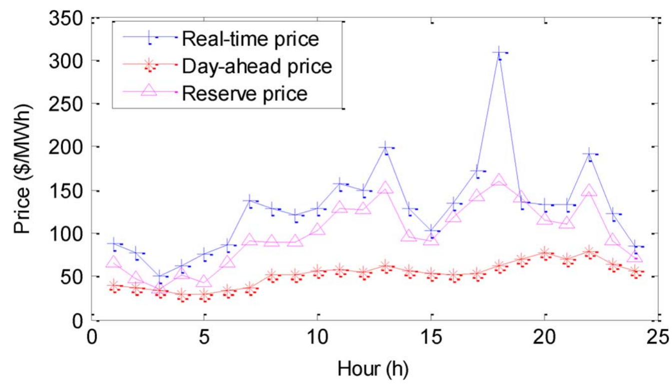

Fig. 12. Case 3: real-time, day-ahead, and settled reserve prices.

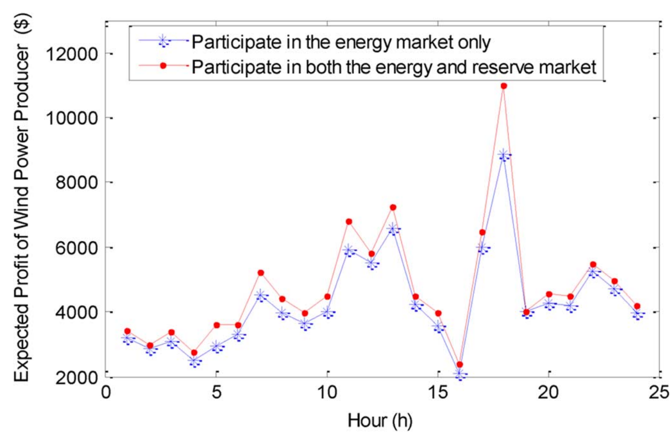

Fig. 13. Case 3: expected profits of the wind power producer.

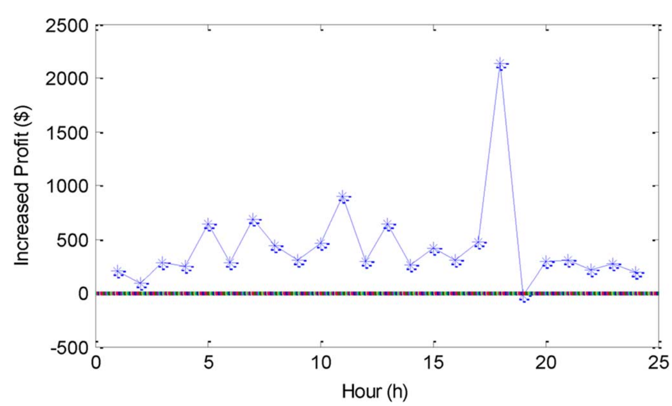

Fig. 14. Case 3: increased profit of the wind power producer from participating in both the energy and bilateral reserve markets.

energy market only and from participating in both the energy and bilateral reserve markets are compared in Fig. 13. The increased profit of the wind power producer from playing a game with other producers in the bilateral reserve market is shown in Fig. 14. The energy market bidding curves of the wind producer in participating in the energy market only and in both the energy and bilateral reserve markets for the 18th and 19th hour

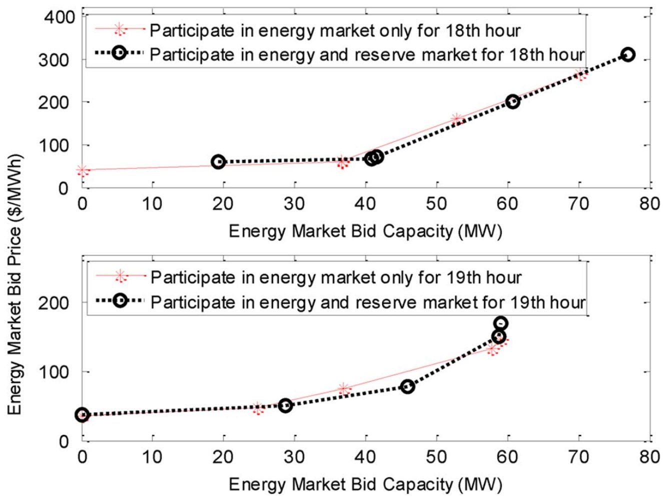

Fig. 15. Case 3: energy market bidding curves of the wind producer generated for the 18th and 19th hour.

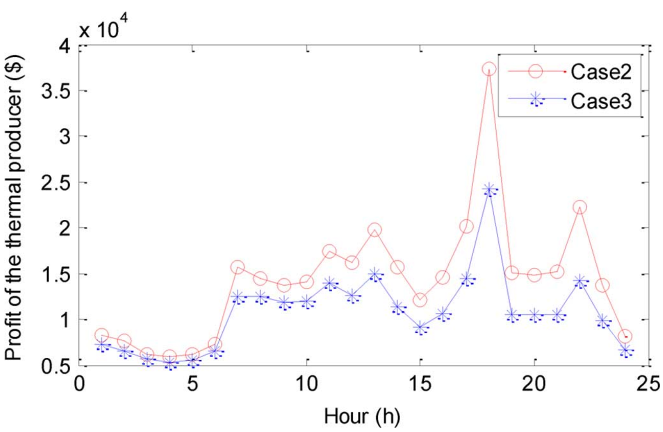

Fig. 16. Expected profits of the thermal units for Cases 2 and 3.

are shown in Fig. 15. The profits of the thermal power producer for Cases 2 and 3 are compared in Fig. 16.

By including the hydro units into the game, the mean value of the reserve price obtained from playing the game during the 24 hours decreases from \$106.17 in Case 2 to \$96.83 in this case. Consequently, the mean value of the expected profit of the wind producer during that day increases from \$4544.8 in Case 2 to \$4729.8 in this case because of the decrease of the reserve price. The participation of the hydro units into the market increases competition, which results in a lower reserve price and more wind power bidden into the energy market. The bidding curves in Fig. 15 show the same trend as in Fig. 7. Moreover, compared with Fig. 11, the bidding curves of the wind producer when participating in both the energy and bilateral reserve markets in Fig. 15 have higher maximum bidding price and bidding capacity.

Fig. 16 clearly shows the influence of the participation of the hydro units on the expected profit of the thermal power producer. Compared to Case 2, the lower reserve price and the increased competition to sell reserve to the wind producer result in a decrease of the profit of the thermal power producer in Case 3. The mean value of the expected profit of the thermal units in Case 3 decreased by 22% with respect to that in Case 2. On the contrary, comparing Figs. 9 and 13, due to the participation of

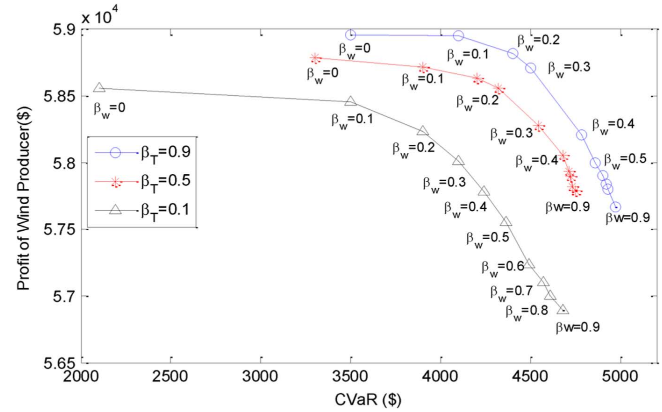

Fig. 17. Expected profit and CVaR for the wind power producer for different β_W and β_T for Case 2.

the hydro units, the mean expected profit of the wind producer in Case 3 increased by 9.7% with respect to that in Case 2.

C. *Impact of Risk Management*

In the previous cases, both β_W and β_T are chosen to be 0.5. To study the impact of risk aversion, the expected profit of the wind producer and the CVaR for different β_W are calculated for Case 2, where β_W changes from 0 to 0.9 with an interval of 0.1. The influence of β_T of the thermal units is also considered. Three curves are plotted in Fig. 17 for β_T to be 0.1, 0.5, and 0.9, respectively, where each curve represents the relationship among the expected profit of the wind producer, CVaR, and β_W.

As shown in Fig. 17, the three curves have the same trend: when β_W increases, the value of CVaR increases but the expected profit decreases. In the case of $\beta_T = 0.5$, the CVaR increased by approximately 43% while the expected profit only reduced by 1.7% when β_W increases from 0 to 0.9. When β_T increases but β_W remains constant, both the expected profit and CVaR increase. This is expected. Since when β_T increases, the thermal units are willing to take less risk by selling more reserve to the wind producer, which increases the expected profit of the wind producer.

The impact of the risk-aversion parameters for Cases 1 and 3 is similar to that of Case 2.

V. Conclusion

The uncertainty in production is the major obstacle for wind power producers to compete with conventional power producers in a competitive electricity market. A joint energy and bilateral reserve market model for trading wind power has been proposed in this paper to help wind power producers deal with their production uncertainties. In the proposed model, stochastic programming has been applied to generate optimal bidding strategies to obtain the maximum expected profits for wind producers in the energy market. Game theory has been applied to take consideration of the uncertainty of other participants' behaviors in a market for trading a new type of reserve settled among wind and conventional power producers. The reserve price is then settled by solving Nash Equilibrium. During normal hours, the expected reserve price is settled between the day-ahead price and real-time price. Wind producers will benefit from buying

cheaper reserve power to reduce or avoid higher real-time penalties as well as to reduce the cost for negative energy deviations in the real-time market. More participants in the new bilateral reserve market will increase the competition and, therefore, decrease the reserve price. Wind producers can benefit more from the bilateral reserve market with diversified reserve suppliers. Case studies using real-world market data have shown that the proposed model is effective for wind producers to actively participate in a competitive electricity market to maximize their profits.

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