Incentive-Based Coordination Mechanism for Renewable and Conventional Energy Suppliers

Sadra Babaei, *Student Member, IEEE*, Chaoyue Zhao, *Member, IEEE*, Lei Fan, *Member, IEEE*, and Tieming Liu

***Abstract*—This paper proposes an incentive-based coordination mechanism between a wind energy supplier (WES) and a conventional energy supplier (CES) to achieve a Pareto improvement. To comply with its day-ahead schedules and hedge against the intermittent wind energy generation, the WES is allowed to outsource a back up power capacity from the CES via making a bilateral contract. However, unanimous agreement cannot always be achieved since each party plays on its own interest. We employ the concept of swing option contracts to further encourage the suppliers to reach an agreement of the contract. On the one hand, the WES can leverage the uncertainty of wind output by covering possible energy shortage from the CES. On the other hand, the CES can optimally allocate its energy capacity by participating into the electricity market and offering capacity to backup the shortage of energy from the WES. The bidding problem for each supplier is formulated as a multi-stage stochastic programming model, with the objective of maximizing the expected profit while maintaining a low level of risk. Unlike the traditional two-stage approach, the proposed multi-stage model can effectively capture the impact of rebidding process in the real-time market. We incorporate conditional-value-at-risk as a risk measure to characterize the effect of risk perception of suppliers on their bidding decisions. Meanwhile, a game theory based approach is developed to obtain the contract items between the suppliers. Implementation results on real cases are provided to illustrate the effectiveness of our proposed framework.**

***Index Terms*—Bilateral contracts, conditional-value-at-risk, game theory, multistage stochastic programming, self-scheduling, wind energy.**

NOMENCLATURE

A. Sets

$\mathcal{G}$	Set of generators.
$\mathcal{I}$	Set of day-ahead price realizations.
$\mathcal{K}$	Set of whole scenarios including market prices and wind outputs.
$\mathcal{N}^+(n)$	Set of child nodes of node n.
$\mathcal{N}_t$	Set of nodes in the scenario tree at time period t.
$\mathcal{T}$	Set of time periods.

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S. Babaei, C. Zhao, and T. Liu are with the School of Industrial Engineering and Management, Oklahoma State University, Stillwater, OK 74074 USA (e-mail: sadra.babaei@okstate.edu; chaoyue.zhao@okstate.edu; tieming.liu@okstate.edu).

L. Fan is with the Software Engineer, Siemens Industry, Inc., Minnetonka, MN 55305 USA (e-mail: lei.fan@ieee.org).

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B. Parameters

$F_c(.)$	Cost with respect to the generation level.
L_g	Minimum power output of generator g.
RD_g	Ramp-down rate for generator g.
RU_g	Ramp-up rate for generator g.
SD_g	Shut-down cost for generator g.
SU_g	Start-up cost for generator g.
U_g	Maximum power output of generator g.
W^{Max}	Installed capacity of the wind farm.
α	Confidence level.
γ	Risk preference parameter.
μ_k	Probability of occurrence of the whole scenario (including market prices and wind outputs) k.
π^i_{tn}	Probability of nth realization of real-time parameters (wind output and real-time market price) in scenario tree at time period t corresponding to the day-ahead price realization i.
ρ_i	Probability of scenario i occurrence for the day-ahead price.

C. Decision Variables

$\mathrm{Ct}^{\mathrm{C},DA}$	Cost of CES from DA market.
$\mathrm{Ct}^{\mathrm{C},RT}$	Cost of CES from RT market.
$\mathrm{Ct}^{\mathrm{W},DA}$	Cost of WES from DA market.
$\mathrm{Ct}^{\mathrm{W},RT}$	Cost of WES from RT market.
$\mathrm{Rv}^{\mathrm{C},DA}$	Revenue of CES from DA market.
$\mathrm{Rv}^{\mathrm{C},RT}$	Revenue of CES from RT market.
$\mathrm{Rv}^{\mathrm{W},DA}$	Revenue of WES from DA market.
$\mathrm{Rv}^{\mathrm{W},RT}$	Revenue of WES from RT market.
o_{tg}	Binary variable to indicate if generator g is on at time period t.
S_t	Backup capacity level at time period t.
s_{tg}	Backup capacity provided by the generator g at time period t.
u_{tg}	Binary variable to indicate if generator g is started up at time period t.
v_{tg}	Binary variable to indicate if generator g is shut down at time period t.
w_t	Unit execution price at time period t.
x^i_{tgn}	Real-time generation amount at time period t by generator g in node n of the scenario tree corresponding to the day-ahead price realization i.
y^{DA}_{tg}	Power offered by the conventional generator g in day-ahead market at time period t.

$y_{tgn}^{RT,i}$ Power offered by the conventional generator g in real-time market at time period t in node n of the scenario tree corresponding to the day-ahead price realization i.

$z_{tn}^{C,i}$ Wind power output curtailed by the wind supplier in real-time market at time period t in node n of the scenario tree corresponding to the day-ahead price realization i.

z_{it}^{DA} Power offered by the wind supplier in day-ahead market for time period t and scenario i.

$z_{tn}^{RT,i}$ Power offered by the wind supplier in real-time market at time period t in node n of scenario tree corresponding to the day-ahead price realization i.

$z_{tn}^{S,i}$ Power purchased by the wind supplier from real-time market at time period t in node n of the scenario tree corresponding to the day-ahead price realization i.

$z_{tn}^{U,i}$ Power utilized by the wind supplier from bilateral contract at time period t in node n of scenario tree corresponding to the day-ahead price realization i.

δ_k Auxiliary variable in scenario k for linearizing of conditional-value-at-risk.

θ_t Unit reservation price at time period t.

ξ Auxiliary variable for calculating conditional-value-at-risk.

D. Random Parameters

W_{tn}^i Wind power production at time period t in node n of the scenario tree corresponding to the day-ahead price realization i.

β_t^i Proportion of backup capacity that is actually utilized by wind supplier at time period t corresponding to the day-ahead price realization i.

κ_{tn}^i Real-time market price at time period t in node n of the scenario tree corresponding to the day-ahead price realization i.

λ_{ti} Day-ahead market price at time period t and scenario i.

I. Introduction

RENEWABLE energy, especially wind energy, has been increasing penetration into power systems. Projections revealed by National Renewable Energy Laboratory reflect that nearly 80% of the electricity will be served by renewable resources to satisfy hourly-based demands in every region of U.S. by 2050 [1]. To promote the growth of renewable energy generation, many European countries and U.S. have established incentive policies like renewable portfolio standard in their electricity markets. As a consequence of these regulations, several U.S. Independent System Operators (ISOs), such as MISO and ERCOT, allow for the participation of renewable power suppliers, particularly Wind Energy Suppliers (WESs), in their electricity markets [2]. A WES confronts with two kinds of uncertainties when it submits energy bids to the market: price and wind power output uncertainties. If the WES is not able to deliver what it commits to the electricity market due to the wind output intermittency, it will face considerable penalty costs for its energy shortage. There are a few options for the WES to mitigate the intermittency or to cover the shortage, but they all have their own limitations.

The first option for the WES is to utilize energy storage resources such as pumped-storage units [3], batteries [4], and air compressed [5] to mitigate its energy shortage risk. However, the energy storage capacities are usually very expensive, and the high costs hinder large-volume installations. The second remedy approach is to purchase energy from the energy market in the form of ancillary services. The main drawback of this strategy is that the system operator does not guarantee the provision of enough power to cover the WES's shortage, due to uncertainties from both the supply and the demand sides. Moreover, more deployments of ancillary services will increase the market clearing price of these services and lead to higher total costs [6]. The hybrid wind-conventional system like wind-thermal ([7], [8]) is examined as another approach. [8] proposes a wind-thermal coordinated trading mechanism for the day-ahead energy market. The problem is formulated as a two-stage stochastic optimization model to maximize the total profit when wind plants are included in the generation portfolio of strategic producers. [9] investigates the expansion planning strategy of quick start generators, like gas-fired generators with flexible minimum up/down and large ramping capabilities, to accommodate the fluctuations of wind generation. However, these generators are often associated with significant operating costs. Another solution for the WES to mitigate wind power output uncertainty is to outsource a backup capacity from a Conventional Energy Supplier (CES) ([10], [11]). For instance, Wartsila Corporation delivered 203 MW gas power plant near San Antonio, Texas to South Texas Electric Cooperative to provide backup power for their customers in 65 counties, where an increasing penetration of wind power brought challenges to the grid stability [12]. In [11], a trading strategy between WES and CES based on a two-stage stochastic programming model is introduced. However, the designed contractual terms are not flexible enough in the sense that the power delivery from CES to WES is unconditional. More particularly, because of wind uncertainty and aversion to charging imbalance penalties, WES is willing to arrange flexible orders from CES. That is, WES would prefer purchasing backup power from the market directly to executing the contract with CES if the contract price is higher than the market price. But the contract proposed in [11] obligates WES to trade the capacity level predetermined in the contract.

Existing literatures on optimal bidding strategies for the WES mostly formulate the problem as a two-stage stochastic programming model (see e.g., [13], [14], [15], [16], among others). According to the two-stage stochastic programming model, in the first stage, the WES submits its bidding in the day-ahead (DA) market before the wind power output and the prices of DA and real-time (RT) markets become known. While in the second stage, the WES decides on its transactions in the RT market once the wind output and DA prices are available and only RT prices are unknown. The RT bidding for all hours of the operating day are made simultaneously at the beginning of the day. Hence, this two-stage approach does not allow any flexibility in real-time decisions after revealing the realization of uncertain parameters during each time period. Moreover, this approach fails to appropriately represent current practices of dependencies among successive periods of wind power outputs since it assumes that the wind output scenarios for the entire operating day are available at the beginning of the day. Recently, a two-step procedure approach is proposed in [17] for bidding strategy of a WES and the Conditional-Value-at-Risk is employed to manage the risk of its profit. In the first step, the bidding strategy for the DA market is decided. Then in the second step, once the actual scheduling in the DA market is identified, the WES derives the bidding strategy in the RT market for each hour of the day separately. Meanwhile, the WES can update the scenarios as new information is observed. However, this paper neglects the impacts of hourly-based RT decisions on the DA biddings.

As the preliminary study of this research, a coordination mechanism between the CES and WES is designed in [18], where the optimal bidding strategy problem is modeled using the traditional two-stage stochastic approach. To the best of our knowledge, this is the first paper that formulates the optimal bidding and contract strategy for a wind energy supplier as a multi-stage stochastic programming model. In our model, the real-time decisions are made in each period on a period basis according to the revealed real-time price and available wind output in that period. In this way, the suppliers have the opportunity to update their real-time decisions as time progresses and more information about the uncertain parameters becomes available. Furthermore, the proposed approach uses an incentive-based mechanism to compensate the WES's energy shortage. Particularly, a two-part structured bilateral contract is developed to allow Pareto improvements to both sides in response to the uncertain market changes. Our designed bilateral contract between the CES and WES is characterized by three main parameters: backup capacity level, reservation price, and execution price. Backup capacity level is the amount of energy that CES committed to deliver to WES upon its request. Reservation price is an allowance paid by WES to CES for reserving one unit of capacity. The execution price is paid by WES to CES for actually using a unit of capacity. This trading mechanism is similar to the swing option contracts ([19]–[22]). In order to obtain the contract parameters between these two suppliers, we employ a game theory framework, which can guarantee the maximum achievable profits. The main contributions of this paper can be listed as follows.

1) We develop a multi-stage stochastic programming to assist both suppliers to optimally submit their bids in the day-ahead and real-time markets. By capturing dependencies between electricity prices as well as wind outputs in consecutive time periods and allowing the suppliers to rebid in the real-time market, our model gives more efficient solutions than the two-stage model.
2) Using swing option contracts, our proposed framework provides flexible contracts to motivate the suppliers to reach an agreement. Meanwhile, it achieves maximum achievable profits for two parties considering operational limitations imposed on the suppliers.
3) We incorporate Conditional-Value-at-Risk (CVaR) into the proposed multi-stage model to provide a useful tool for the suppliers with various risk attitudes, from risk-neutral to risk-averse. In other words, our model generates optimal bidding strategies based on the suppliers' conservativeness levels.

The remainder of the paper is organized as follows. In Section II, we describe the market clearing process in the two-settlement electricity market. In Section III, we derive multi-stage stochastic programming models to describe the optimal bidding strategies for both CES and WES. Furthermore, we investigate the solution methodology and procedure for exploring Nash equilibrium in Section IV. In Section V, we provide case studies and conduct computational experiments. Finally, we conclude this study in Section VI.

II. Problem Description

A. Market Framework

In U.S. electricity markets such as MISO and CAISO, market participants can submit energy bids in both day-ahead and real-time markets [2]. The day-ahead market is a one-time bidding process, while the real-time market consists of sequentially bidding processes for each hour. Hence, knowing the price of previous hours, market participants have the opportunity to update the bid prior to the deadline of each operating hour. Market participants can submit their bids to the ISO in different modes. We investigate a paradigm in which the suppliers submit offers in the form of self-scheduling. In the self-scheduling mode [23], the supplier is responsible for its commitment and generation level for each time period and it only submits energy quantities to the ISO, instead of quantity-price bid pairs. In this paper, we assume that CES and WES can establish a bilateral contract. This agreement can provide a hedging mechanism for both suppliers. That is, the CES is allowed to allocate its energy capacity by submitting bids to the day-ahead market and real-time market, and backing up the WES's energy shortage, based on the market price and the contract price. Similarly, the WES can also participate in the markets by buying or selling its energy and covering its energy shortage with the backup capacity provided by the CES. On one hand, this mechanism creates an incentive for the WES to accommodate wind output uncertainty and to avoid energy shortage penalties. On the other hand, pre-committing capacity to WES via a bilateral contract yields to a wise utilization of capacity and a recovery of underlying costs for the CES in the presence of unknown market price.

B. Uncertainty Characterization

We consider three uncertainty parameters in our model: day-ahead (DA) market price, real-time (RT) market price, and wind energy production. A multi-stage scenario tree is developed to describe the possible realizations of uncertain parameters. The multi-stage scenario tree can effectively capture the correlation of wind outputs as well as RT market prices among different time periods. For example, Fig. 1 illustrates a scenario tree for the WES. Each node, except the root node, corresponds to a real-time decision and each branch corresponds to a realization of random parameters. The root node can be

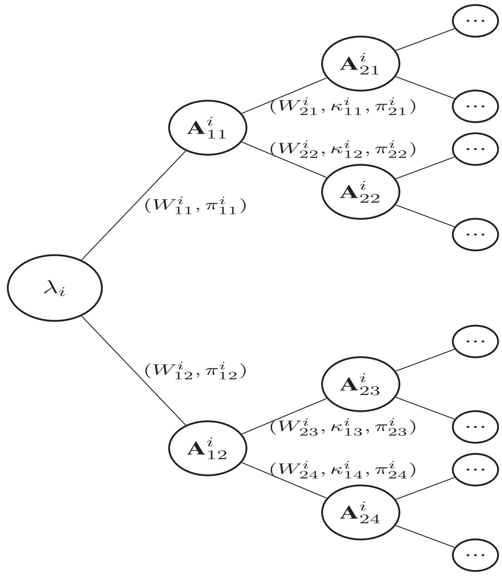

Fig. 1. Multi-stage scenario tree for a realized day-ahead market.

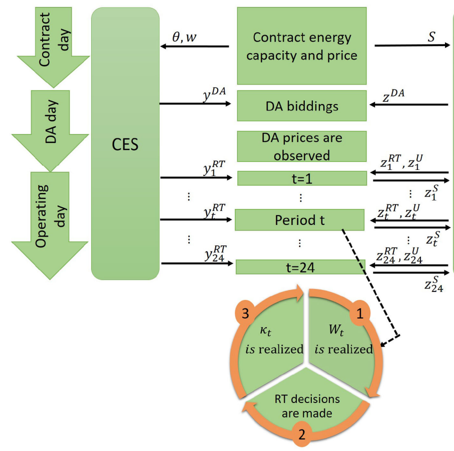

Fig. 2. The market timeline and decision making process.

interpreted as a realized DA price. For the ith observation of the DA price, the wind energy for the first hour with its corresponding probability is realized at branches (W_{11}^i, π_{11}^i) and (W_{12}^i, π_{12}^i). Then, the WES decides on the amount of energy transactions with CES or market operator at nodes $\mathbf{A}_{11}^i$ and $\mathbf{A}_{12}^i$ to offset its possible energy deficit. Branches $(W_{21}^i, \kappa_{11}^i, \pi_{21}^i)$, $(W_{22}^i, \kappa_{12}^i, \pi_{22}^i)$, $(W_{23}^i, \kappa_{13}^i, \pi_{23}^i)$, $(W_{24}^i, \kappa_{14}^i, \pi_{24}^i)$ represent four samples $(W_{21}^i, W_{22}^i, W_{23}^i, W_{24}^i)$ of the wind outputs in the second hour and four samples $(\kappa_{11}^i, \kappa_{12}^i, \kappa_{13}^i, \kappa_{14}^i)$ of the RT prices in the first hour with their associated probabilities $(\pi_{21}^i, \pi_{22}^i, \pi_{23}^i, \pi_{24}^i)$. Correspondingly, decisions for the second hour are made at nodes $\mathbf{A}_{21}^i$, $\mathbf{A}_{22}^i$, $\mathbf{A}_{23}^i$, $\mathbf{A}_{24}^i$. This procedure will continue until the last operating hour. Note here that the RT decisions corresponding to each node n are made after observing the realizations of wind outputs and RT prices along the path from the root node to the node n. Thus, the uncertainties at each period in node n are wind outputs for the next periods as well as RT prices for the current and oncoming periods.

C. Assumptions

We make the following assumptions about the model:

- Both suppliers' strategies and payoff functions are public information. In other words, each supplier has complete knowledge about the strategies and payoffs of the other supplier, but not the decisions.
- The operation cost for the WES is negligible.
- Both WES and CES are considered to be price-takers in the day-ahead and real-time markets. This means both suppliers have no market-power in the energy markets and therefore, their offers have no impact on the market clearing price. This is a reasonable assumption since we assume both WES and CES hold small shares of generation compared to the total generation in the market.
- All bids will be accepted in the market. In other words, the suppliers can bid a low price along with their generation quantities to ensure that their bids will be accepted.

D. Decision Sequence

The market timeline and decision making process in our framework can be summarized as follows:

1) The WES and CES sign a bilateral contract.
2) One day prior to the operating day, the WES and CES submit their bids into the DA market for all hours simultaneously.
3) The ISO clears the DA market and releases the DA price to the suppliers.
4) Closing to its actual energy delivery for time period t in the operating day, the WES identifies its wind output for period t.
5) The suppliers submit their biddings and offerings in the RT market for period t. Additionally, the WES determines how much energy to be utilized from its reserved capacity in the contract for period t.
6) The ISO clears the RT market for period t and announces the price for this hour.

Steps 4–6 are repeated until the last time period in the operating day. Fig. 2 illustrates the above decision sequence.

III. Mathematical Formulation

In this section, we formulate the optimal bidding problems for both conventional and wind energy suppliers, which can participate in the wholesale electricity markets and make a bilateral contract with each other. We adopt a multi-stage stochastic programming approach to model the self-scheduling process for both CES and WES in the day-ahead and real-time markets. Since stochastic programming is inherently a risk-neutral approach, we incorporate Conditional-Value-at-Risk (CVaR) as a risk measure in our model to manage the financial risk of the suppliers. By definition, with respect to a specified confidence level α, CVaR_α is the conditional expectation of profits below the $(1-\alpha)$-percentile of the profit distribution. The

$(1-\alpha)$-percentile of the profit distribution is known as Value-at-Risk (VaR), which is the largest value that guarantees the profit falls below that value only with a small probability $(1-\alpha)$. Mathematically speaking, CVaR is evaluated by the following equation:

$$\mathrm{CVaR}_\alpha = \mathbb{E}\left[\text{profit}\middle|\text{profit} \le \mathrm{VaR}_\alpha\right] \tag{1}$$

For a scenario-based stochastic optimization model, CVaR can be calculated by the following linear optimization problem [24]:

$$\begin{aligned}\mathrm{CVaR}_\alpha =& \max_{\delta\ge 0,\xi}\left\{\xi - \frac{1}{1-\alpha}\sum_{i\in\mathcal{I}}\tau_i\delta_i\right\}\\ \text{s.t.}\quad & \delta_i \ge \xi - X(i),\ \forall i,\end{aligned} \tag{2}$$

where optimal ξ represents VaR, $X(i)$ is the ith scenario of profit with its associated probability τ_i, and δ_i is an auxiliary variable indicating the difference between VaR and the scenario profit, which is positive if the scenario profit is less than VaR, and is zero otherwise. Then, we formulate the problem for both CES and WES as follows.

A. Conventional Energy Supplier

The CES is considered to operate and schedule a number of thermal units. For CES, DA decisions are unit reservation price, unit execution price, online or offline status of generators, start up and shut down decisions, and energy offered to the DA market. The RT decisions at different time periods corresponding to each node in the scenario tree are energy offered to the RT market and energy outputs. Given backup capacity level S provided by WES, the problem of identifying the best bidding and contract strategy for the conventional supplier can be formulated as follows:

$$\begin{aligned}\Pi^C(S) =& \max\ \mathbb{E}\left[\mathrm{Rv}^{C,DA}\right] + \mathbb{E}\left[\mathrm{Rv}^{C,RT}\right]\\ &- \mathrm{Ct}^{C,DA} - \mathbb{E}\left[\mathrm{Ct}^{C,RT}\right] + \gamma_C \mathrm{CVaR}_\alpha\end{aligned} \tag{3}$$

$$\text{s.t.}\ \mathbb{E}\left[\mathrm{Rv}^{C,DA}\right] = \sum_{t\in\mathcal{T}} S_t\theta_t + \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}}\sum_{i\in\mathcal{I}}\rho_i\lambda_{ti}y^{DA}_{tg}, \tag{4}$$

$$\begin{aligned}\mathbb{E}\left[\mathrm{Rv}^{C,RT}\right] =& \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}}\sum_{i\in\mathcal{I}}\rho_i\left[\sum_{n\in\mathcal{N}_t}\sum_{j\in\mathcal{N}^+(n)}\pi^i_{tj}\kappa^i_{tj}y^{RT,i}_{tgn}\right]\\ &+\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}}\rho_i\beta^i_t S_t w_t,\end{aligned} \tag{5}$$

$$\mathrm{Ct}^{C,DA} = \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}}(SU_g u_{tg} + SD_g v_{tg}), \tag{6}$$

$$\mathbb{E}\left[\mathrm{Ct}^{C,RT}\right] = \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}}\sum_{i\in\mathcal{I}}\rho_i\left[\sum_{n\in\mathcal{N}_t}F_c(x^i_{tgn})\right], \tag{7}$$

$$\mathrm{CVaR}_\alpha = \xi - \frac{1}{1-\alpha}\sum_{k\in\mathcal{K}}\mu_k\delta_k, \tag{8}$$

$$L_g o_{tg} \le y^{DA}_{tg} + \mathrm{s}_{tg} \le U_g o_{tg},\ \ \forall t,g \tag{9}$$

$$-o_{(t-1)g} + o_{tg} - u_{tg} \le 0,\ \ \forall t,g \tag{10}$$

$$o_{(t-1)g} - o_{tg} - v_{tg} \le 0,\ \ \forall t,g \tag{11}$$

$$\sum_{g\in\mathcal{G}}\mathrm{s}_{tg} = S_t,\ \ \forall t \tag{12}$$

$$\sum_{g\in\mathcal{G}}x^i_{tgn} = \sum_{g\in\mathcal{G}}y^{DA}_{tg} + \sum_{g\in\mathcal{G}}y^{RT,i}_{tgn} + \beta^i_t S_t,\ \ \forall t,i,n \tag{13}$$

$$L_g o_{tg} \le y^{DA}_{tg} + y^{RT,i}_{tgn} + \mathrm{s}_{tg} \le U_g o_{tg},\ \ \forall t,g,n \tag{14}$$

$$L_g o_{tg} \le x^i_{tgn} \le U_g o_{tg},\ \ \forall t,g,i,n \tag{15}$$

$$\begin{aligned}x^i_{tgn} - x^i_{(t-1)gn} \le& RU_g o_{(t-1)g}\\ &+ U_g(1-o_{(t-1)g}),\ \ \forall t,g,n\end{aligned} \tag{16}$$

$$x^i_{(t-1)gn} - x^i_{tgn} \le RD_g o_{tg} + U_g(1-o_{tg}),\ \forall t,g,n \tag{17}$$

$$\xi - \left[\mathrm{Rv}^{C,DA}_k + \mathrm{Rv}^{C,RT}_k - \mathrm{Ct}^{C,DA}_k - \mathrm{Ct}^{C,RT}_k\right] \le \delta_k,\ \forall k \tag{18}$$

$$\begin{aligned}&u_{tg}, v_{tg}, o_{tg} \in \{0,1\},\\ &\theta_t, w_t, y^{DA}_{tg}, y^{RT,i}_{tgn}, x^i_{tgn}, \delta_k \ge 0,\ \ \forall t,g,n,i,k.\end{aligned} \tag{19}$$

The objective for CES is to maximize the expected profit while maintaining a reasonable level of risk. The risk preference parameter γ_C allows the CES to make a balance between the expected profit and CVaR, and as a result, to generate different bidding strategies. When the value of γ_C is equal to zero, the CES is totally risk-neutral. That means, the CES maximizes its expected profit while it ignores the risk of profit. As the value of γ_C increases, the CES becomes more risk-averse, in the sense that it maximizes both the expected profit and CVaR. Maximizing CVaR is intended to increase the average profit of worst scenarios that encounter with very low probabilities. If the value of γ_C is large enough, the CES only maximizes CVaR to ensure that a minimum level of profit is obtained with a high probability α. The first two terms in the objective function (3) express the revenues of CES and the following two terms indicate the costs of CES from DA and RT markets, respectively. The expected DA revenue is calculated in (4), which includes DA incomes from reserving capacity for WES in the bilateral contract and DA bidding. The expected RT profit in (5) results from RT bidding and providing capacity to WES. We assume that from the historical data, the RT utilized capacity by WES can be estimated as a fraction (i.e., β) of the backup capacity. The DA cost in (6) is associated with the generators start-up/shut-down costs. The RT cost in (7) pertains to the generation cost, which is approximated by a m-piece piecewise linear function. Constraints (9), (14), and (15) enforce the generation capacity on each thermal unit. (10) and (11) represent unit start-up and shut down constraints, respectively. Constraints (12) ensure that the CES provides the required backup capacity to WES. Power balance constraints are expressed in (13). Constraints (16) and (17) impose ramping rate limits for each unit. Finally, constraints (18) calculate CVaR.

B. Wind Energy Supplier

Regarding WES, the DA decisions are backup capacity level and energy offered to the DA market, while the RT decisions associated with each node in the scenario tree are energy offered to the RT market, energy purchased from real-time market, energy utilized from the bilateral contract, and wind outputs that are curtailed. Given unit reservation price θ and execution price w provided by CES, the problem of finding the optimal bidding and contract strategy for the wind supplier can be defined as follows:

$$\Pi^W(\theta, w) = \max \mathbb{E}\left[\mathrm{Rv}^{\mathrm{W},DA}\right] + \mathbb{E}\left[\mathrm{Rv}^{\mathrm{W},RT}\right] - \mathrm{Ct}^{\mathrm{W},DA} - \mathbb{E}\left[\mathrm{Ct}^{\mathrm{W},RT}\right] + \gamma_W \,\mathrm{CVaR}_\alpha \tag{20}$$

$$\text{s.t.} \quad \mathbb{E}\left[\mathrm{Rv}^{\mathrm{W},DA}\right] = \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} \rho_i \lambda_{ti} z_t^{DA}, \tag{21}$$

$$\mathbb{E}\left[\mathrm{Rv}^{\mathrm{W},RT}\right] = \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} \rho_i \left[\sum_{n\in\mathcal{N}_t}\sum_{j\in\mathcal{N}^+(n)} \pi_{tj}^i \kappa_{tj}^i z_{tn}^{RT,i}\right], \tag{22}$$

$$\mathrm{Ct}^{\mathrm{W},DA} = \sum_{t\in\mathcal{T}} \theta_t S_t, \tag{23}$$

$$\mathbb{E}\left[\mathrm{Ct}^{\mathrm{W},RT}\right] = \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} \rho_i \left[\sum_{n\in\mathcal{N}_t}\sum_{j\in\mathcal{N}^+(n)} \pi_{tj}^i \kappa_{tj}^i z_{tn}^{S,i}\right] + \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} \rho_i \left[\sum_{n\in\mathcal{N}_t} w_t z_{tn}^{U,i}\right], \tag{24}$$

$$\mathrm{CVaR}_\alpha = \xi - \frac{1}{1-\alpha}\sum_{k\in\mathcal{K}} \mu_k \delta_k, \tag{25}$$

$$0 \le z_t^{DA} \le W^{\mathrm{Max}}, \ \ \forall t \tag{26}$$

$$W_{tn}^i = z_t^{DA} + z_{tn}^{RT,i} + z_{tn}^{C,i} - z_{tn}^{S,i} - z_{tn}^{U,i}, \ \forall t, n, i \tag{27}$$

$$0 \le z_{tn}^{U,i} \le S_t, \ \ \forall t, n, i \tag{28}$$

$$\xi - \left[\mathrm{Rv}_k^{\mathrm{W},DA} + \mathrm{Rv}_k^{\mathrm{W},RT} - \mathrm{Ct}_k^{\mathrm{W},DA} - \mathrm{Ct}_k^{\mathrm{W},RT}\right] \le \delta_k, \ \forall k \tag{29}$$

$$S_t, z_t^{DA}, z_{tn}^{RT,i}, z_{tn}^{C,i}, z_{tn}^{U,i}, z_{tn}^{S,i}, \delta_k \ge 0, \ \ \forall t, n, i, k. \tag{30}$$

Similar to CES, the objective for WES is to maximize the expected profit and CVaR. The first two components in (20) represent revenues of WES from DA and RT markets, respectively, and the following two components represent costs of WES from both markets. The DA and RT revenues in (21) and (22) come from selling energy to the corresponding markets. The DA cost (23) is caused by the reserved capacity from CES and the RT cost (24) stems from actually utilizing the reserved capacity from CES and purchasing energy from the RT market. Constraints (26) limit the power that WES can trade in the DA market. Constraints (27) indicate power balance. That is, the total realized wind output should be equal to the amount of energy offered in the DA as well as RT markets, and wind curtailment minus the amount of energy purchased from CES and RT market. Constraints (28) bound the amount of power transaction in the contract with CES. Finally, constraints (29) evaluate CVaR.

IV. Solution Methodology

Game theory is a powerful framework for analyzing strategic decision situations where the payoff of each individual decision maker relies on the decision of other decision makers. Recent publications in power market area pay more attention to game theory as it conceivably supports competition in the market ([25]–[27]). Market participants are always seeking to know whether they are better off by cooperation or by non-cooperation in competitive markets. A necessary condition for the non-cooperative game is that a binding commitment about price fixing and quantity fixing has to be made in such a way that all participants can benefit from it. The suppliers can play either a pure or mixed strategy game [28]. In the pure game, each supplier can choose only one particular strategy from its strategy set. Unlike the pure games, the mixed strategy games allow for choosing multiple strategies based on an assigned probability distribution. One concern associated with the mixed strategy is that it is not clear how an energy supplier would actually implement a mixed strategy. Accordingly, this is not a good fit for our problem setting, since in our paper, the suppliers should come up with one certain single contract and one plan to optimize their market participation based upon this certain contract. Considering multiple contracts each associated with a probability distribution can cause implementation issues. Therefore, we will focus on the pure strategy game in this study. Notice that the considered game is a nonzero-sum game since the sum of the suppliers objective functions is not zero (even after scaling and translation). Nash equilibrium is a concept solution used in game theory to describe an equilibrium where no participants has any incentive to unilaterally change its own strategy. To demonstrate the mathematical procedure of finding Nash equilibrium, let us assume $S_t^1, S_t^2, ..., S_t^M$ be finite discretization of the set $\mathscr{S}$ of capacity strategies and $(\theta_t^1, w_t^1), (\theta_t^2, w_t^2), ..., (\theta_t^J, w_t^J)$ be finite discretization of the set $\mathscr{P}$ of price contract terms (θ, w). Let us also assume that $\phi^C(\theta, w \mid S)$ indicates the total profit of CES corresponding to its price contract decisions (θ, w), given backup capacity S, and $\phi^W(S \mid \theta, w)$ represents the total profit of WES corresponding to its backup capacity decision S, given price contract strategy (θ, w). If (S^*, θ^*, w^*) is a Nash equilibrium, then none of the suppliers can profitably stray from the strategy (S^*, θ^*, w^*). The algorithm for finding Nash equilibrium is depicted in a flow chart in Fig. 3. Since both sets $\mathscr{S}$ and $\mathscr{P}$ include finite discrete elements and we delete dominated points, the algorithm will terminate in finite number of iterations. Meanwhile, if no Nash equilibrium does exist, then the suppliers do not adopt a contract.

V. Case Study

In this section, we consider one wind plant and one thermal plant including two units. The installed capacity of the wind

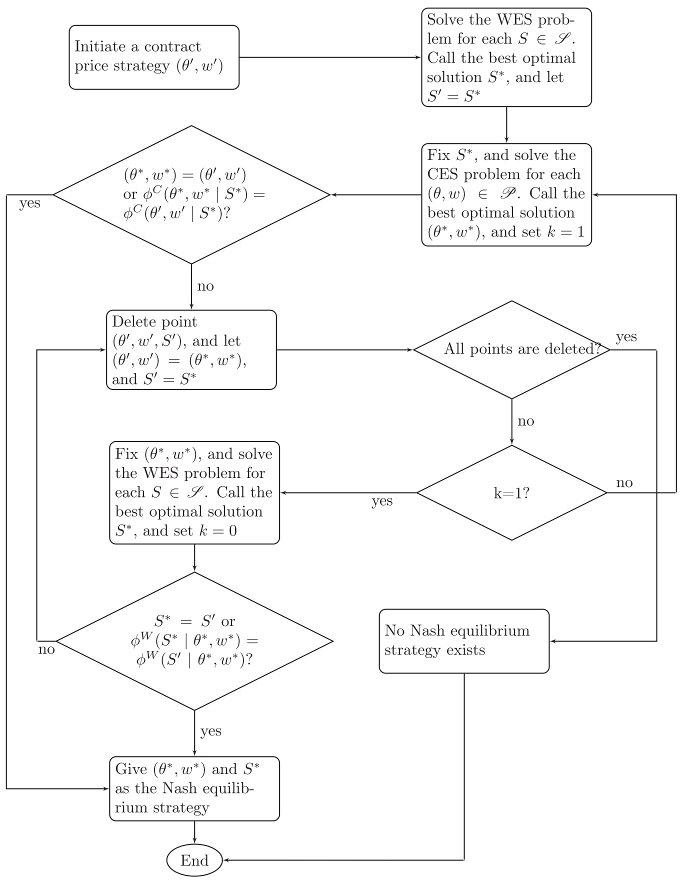

Fig. 3. Flowchart of solution methodology.

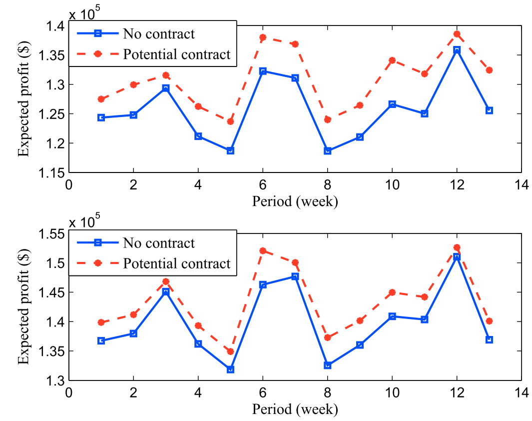

Fig. 4. Expected weekly profits for WES (above) and CES (below).

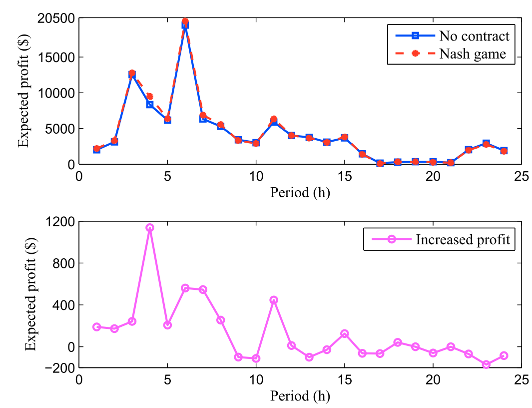

Fig. 5. Expected hourly profits (above) and increased hourly profits (below) from participating in both energy market and bilateral contract for WES.

plant and thermal plant are 100 MW and 130 MW, respectively. We use the historical market price data during January 1-November 1, 2014 from the MISO-Michigan hub. We exclude weekend data to preclude any weekly seasonality. DA and RT price samples are generated using the procedure proposed in [29], and the wind output samples are simulated using the method applied in [30]. Moreover, for multi-stage scenario tree construction and real-time scenario reduction, we employ the method proposed in [31]. We conduct several experiments with different scenario sizes. Unless state otherwise, the day-ahead and real-time sample sizes are 50, and the corresponding multi-stage real-time scenario tree includes 932 nodes. The confidence level is set at $\alpha = 0.9$ to calculate CVaR. All of the experiments are implemented in C++ and solved with CPLEX 12.6 on a computer with Intel Xeon 3.2 GHz and 8 GB memory. We concentrate more on the behavior of WES in the case studies. In the following part, we first verify the effectiveness of the proposed trading mechanism by giving several numerical examples. Second, we compare our multi-stage stochastic programming model with the two-stage stochastic model.

A. *Effects of Signing Contract*

To assess the proposed method, out-of-sample simulations are carried out in daily time steps over a 13-week horizon. The expected weekly profits of the suppliers are compared in two different scenarios as shown in Fig. 4. The first scenario (no contract) is that the suppliers participate in the energy market only. The second (potential contract) is that the suppliers have the option to transact with each other in addition to participating in the market. From Fig. 4, we can see that the expected weekly profits obtained in the second scenario are always superior to those obtained in the first scenario. This means both CES and WES benefit from conducting the contract. Yet the differences in some weeks (e.g., weeks 3 and 12) are smaller since the contract is not exercised for some days during the corresponding weeks. To better understand the details of the transaction mechanism, in the following we concentrate on a specific day of the planning horizon, in which the contract is signed.

The expected hourly profits of the WES are illustrated in Fig. 5. It can be observed that having transaction with the CES brings more benefits to the WES as its total increased profit is \$3085, with increment rate of 3.1%. We notice that the CES also finds the bilateral contract viable with totally 2.5% increment rate. Fig. 5 also shows that the WES mostly gets advantage from the contract at time period 4. The reason is that the volatile RT market price becomes pretty high at this period and thus the WES inclines to utilize its backup capacity from the CES instead of buying energy from the RT market with higher price. On the other hand, we observe that the profit of the first scenario (not engaging in the contract) is slightly greater than the

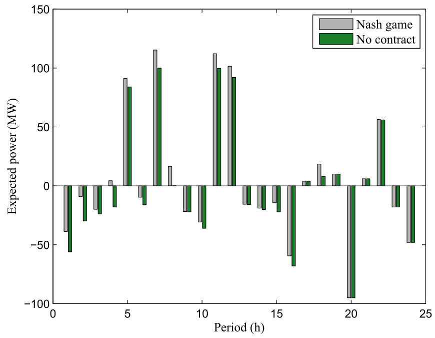

Fig. 6. Expected hourly power traded with RT market for WES.

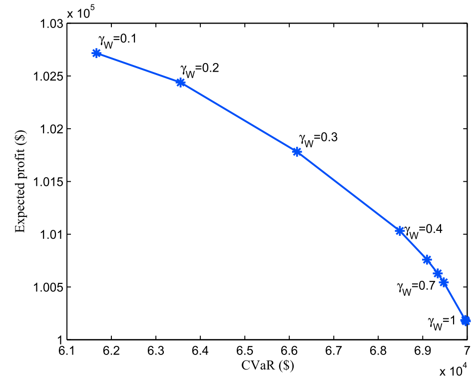

Fig. 7. Expected profit versus CVaR for WES considering different risk perceptions.

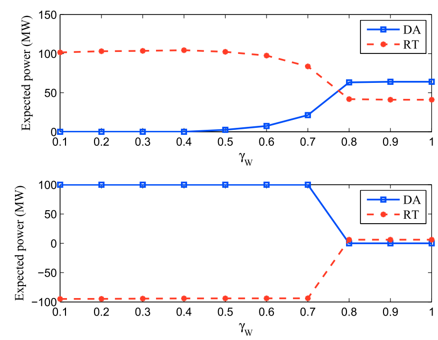

Fig. 8. Expected power traded by WES in DA and RT markets for time period 12 (above) and time period 20 (below).

second one (Nash game case) during some periods. For instance in time period 23, the execution price w_{23} is greater than the RT market price. Thus, the WES has no tendency to exercise the contract. However, since it has already paid $\theta_{23} S_{23}$ for reserving the backup capacity, adopting the contract yields to a less profit for the WES at this period. It is worthy to mention that for some periods the WES has no wish to use the backup, like time period 23. Therefore, our two-part price bilateral contract (swing option contract) provides a more cost-effective solution compared to the traditional one-part price contract (forward contract). The reason is that our contract represents the right, but not the obligation, to purchase power at the prearranged execution price. Hence, when the market price is less than the execution price, the WES does not exercise the contract, but purchase the energy from the market with the market price to recover the shortage, plus a reservation price (reservation price usually contains a small portion of the execution price) paid to CES for reserving the capacity. However, the forward contract obligates the WES to purchase from the CES, though the contract price is higher than the market price. Therefore, the forward contract might be more costly to the WES. In other words, by considering the reservation price in the contract, the risk is more diversified between the suppliers and the WES is further motivated to sign the contract.

Fig. 6 indicates the expected energy traded in the RT market for each time periods. For periods that the expected DA price is higher than the RT price, the WES decides to bid into the DA market as much as possible and then recover its energy shortage by trading with CES and RT market. In this case, the bilateral contract provides a precious opportunity for WES to purchase less expensive power from the RT market. Moreover, for the periods that the RT price is higher than the DA price, the WES prefers to assign all of its capacity into the RT market. In this case, the contract allows the WES to utilize the backup capacity with low price and sell it to the RT market with higher price. For other periods like time periods 23 and 24, we can readily identify that the power traded in the RT market for Nash game and no contract cases are the same. The reason is that it is not economically justifiable for the WES to use its backup capacity. Considering above discussion, it can be clearly observed that our devised bilateral contract provides a flexible tool for the WES to secure itself with respect to the uncertainties in the operating day.

B. Effects of Risk Perception

Fig. 7 shows the efficient frontier for the WES. Efficient frontier plays a crucial role for the WES to resolve the trade-off between the expected profit and risk. For a low risk-averse behavior of WES ($\gamma_W = 0.1$), the value of expected profit is \$102716 with CVaR of \$61663. By moving to a high risk-averse case ($\gamma_W = 1$), the value of CVaR grows by 13.5% at the cost of just 2.4% reduction in the expected profit. This is a compelling result since by a small decline in expected profit, the risk of profit volatility is significantly reduced.

Fig. 8 illustrates the impact of various risk attitudes on the amount of power that WES trades with the DA and RT markets for time periods 12 and 20. We choose these periods as they reveal two distinct properties. The wind output is highly volatile in time period 12 and the expected RT price is greater than the DA price. However, the wind output has less fluctuations in time period 20 and the DA price is greater than the RT price. Considering time period 12, as the WES becomes more risk-averse (the value of γ_W increases), it offers more power in the DA market and less in the RT market to hedge against the rise in RT price. In contrast, the WES has tendency to trade less power in the DA and more in the RT markets for time period 20. By this strategy, the WES lowers its profit volatility in the hope that it can sell its generation in the RT market at a reasonable high price.

TABLE I
COMPARING OBJECTIVE VALUES FOR MULTI-STAGE AND TWO-STAGE STOCHASTIC PROGRAMMING

DA		50				100			
RT		50		100		50		100	
Instance		Two	Multi	Two	Multi	Two	Multi	Two	Multi
Day 1	profit($)	147587	148018	144620	144694	138872	139283	139429	139450
	time(s)	10.29	84.73	10.05	129.11	9.6	211.38	11.94	333.16
Day 2	profit($)	140049	140348	137870	138105	113004	113263	112537	112720
	time(s)	12.21	87.55	11.17	108.72	10.59	195.71	11.16	255.91
Day 3	profit($)	129962	143016	130792	144321	136225	149022	134446	147613
	time(s)	23.04	92.18	19.48	110.39	20.19	205.14	23.11	342.1
Day 4	profit($)	130506	131204	128988	129767	117397	118312	116864	117710
	time(s)	11.62	81.27	13.77	162.13	19.45	198.21	20.1	232.93

C. Effects of Multi-Stage Programming

In order for evaluate the performance of our multi-stage stochastic programming model, we compare the results with the two-stage stochastic case. We carry out case studies for 4 different days, with DA price samples of two sizes (50,100), and RT price as well as wind output samples of two sizes (50,100). According to the Table I, the expected profits attained by the multi-stage model are always superior respect to those attained by the two-stage model. This is because the multi-stage solution comes up with more flexibility in RT decisions with respect to the uncertain parameter realizations. However, there is a trade-off between flexibility and computational efficiency, when using the multi-stage model.

VI. Conclusion

We develop a multi-stage stochastic programming model for the wind and conventional energy suppliers to optimize their bidding strategies in the both day-ahead and real-time markets. Our proposed model provides an opportunity to the wind supplier to update its real-time decisions as time progresses when more information about wind outputs and real-time market prices become available. In addition, using option contract with Nash equilibrium framework, an incentive-based trading mechanism is investigated to help the wind energy supplier to recover its energy deficit and at the same time bring the conventional energy supplier to obtain more profits. The computational results verify that our proposed approach is effective in accommodating wind and price uncertainties. Finally, as the future work of this paper, our framework can be extended to the case with one conventional supplier and several renewable suppliers, and the case with several conventional suppliers and one renewable supplier.

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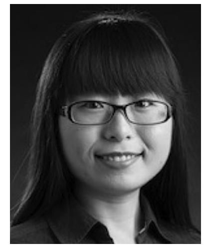
Sadra Babaei (S'17) received the B.S. degree in industrial engineering from Iran University of Science and Technology, Tehran, Iran, in 2009, and the M.S. degree in industrial engineering from Amirkabir University of Technology, Tehran, Iran, in 2012. He is currently working toward the Ph.D. degree with the School of Industrial Engineering and Management, Oklahoma State University, Stillwater, OK, USA. His research interests include decision making under uncertainty and data-driven optimization with their applications in power system operations and renewable energy integration.



Chaoyue Zhao (M'12) received the B.S. degree in information and computing sciences from Fudan University, Shanghai, China, in 2010, and the Ph.D. degree in industrial and systems engineering from the University of Florida, Gainsville, FL, USA, in 2014. She is an Assistant Professor in industrial engineering and management with Oklahoma State University, Stillwater, OK, USA. She was with Pacific Gas and Electric Company in 2013. Her research interests include data-driven stochastic optimization and stochastic integer programming with their applications in power grid security and renewable energy management.

Lei Fan (S'13–M'15) received the B.S. degree in electrical engineering from Hefei University of Technology, Hefei, China, in 2009, and the Ph.D. degree in industrial and systems engineering from the University of Florida, Gainesville, FL, USA, in 2015. He was an Application Engineer in General Electric from 2015 to 2017. He is currently a Software Engineer with Siemens Industry, Inc., Minnetonka, MN, USA. His research interests include the optimization of power system operations, planning, and energy market analysis.

Tieming Liu received the B.S. and M.S. degrees in automation from Tsinghua University, Beijing, China, in 1997 and 2000, respectively, the M.S. degree in industrial engineering and management science from Northwestern University, Evanston, IL, USA, in 2001, and the Ph.D. degree in transportation and logistics from Massachusetts Institute of Technology, Cambridge, MA, USA, in 2005. He is currently an Associate Professor with the School of Industrial Engineering and Management, Oklahoma State University, Stillwater, OK, USA.