Research Article

Bidding Strategy of a Wind-Thermal GENCO considering Piecewise Linear AC Power Flow and Correlated Uncertainties

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In deregulated electricity markets, generation companies (GENCO) try to maximize their economic benefits considering the electricity demand, transmission network condition, and other participants’ behaviors. The increasing penetration of renewable sources such as wind power generation with intermittent nature poses several challenges to the participation of GENCOs in the electricity market. Thus, this paper presents a stochastic bilevel optimization model to determine the coordinated bidding strategy of a wind-thermal GENCO with the aim of maximizing its profit in the day-ahead and real-time balancing market. Herein, the model aims to maximize the profit of GENCO in the day-ahead and the balancing market in the upper-level problem while minimizing the operation cost of the system in the lower-level problem. The uncertainties of wind power generation and electricity demand are modeled by defining a set of scenarios considering their mutual correlation using the copula technique. Additionally, incorporating AC power flow constraints in the proposed optimization model offers a better solution to the coordinated bidding strategy of the wind-thermal GENCO. Further, the nonlinear AC power flow equations are linearized using the piecewise approximation technique to reduce the computational complexity and enhance the accuracy of the optimal solution. In the end, the developed algorithm is implemented on the IEEE 24-bus RTS, and the simulation results are provided to validate the efficiency and applicability of the proposed coordinated bidding strategy model. The results advocate that the participation of the thermal unit along with the wind farm might mitigate the risk of uncertainties, but it causes an intense increase in the locational marginal price of the system. Importantly, the simulation results indicate the computational efficiency of the model by developing an exact AC power flow model without compromising the results. Notably, it has been found that the profit of the wind-thermal GENCO would be increased by 35.2% employing the copula technique to model the mutual correlation of uncertain parameters.

1. Introduction

1.1. Aim. The intense increase in fossil fuel prices and environmental concerns of greenhouse gases (GHG) has made policy-makers and power system planners find alternatives for conventional thermal and gas power plants [1, 2]. In recent decades, exploiting renewable energy sources (RE斯) in the generation sector of power systems has been increasing rapidly [3, 4]. The leading technologies of RE斯 include wind and solar power, hydropower, biomass, and geothermal [5, 6]. A remarkable penetration of wind power, among other technologies, has been realized in the last decade [7]. The total deployed capacity of wind power at the end of 2019 was 651 GW worldwide, which means more than 10% growth compared to 2018 [8]. However, the intermittency and unpredictability nature of wind power poses significant challenges in the power system’s operation [9].

In a restructured environment with competitive electricity markets, the generation companies (GENCO) determine the optimum bidding strategy for participating in the wholesale electricity market [10]. The main goal of market participants in the electricity market is maximizing their profit considering the prevailing uncertainties [11]. For a GENCO with thermal power plants, merely the market-
Literature Review. In the literature, several works have investigated the bidding strategy of producers (with and without RES penetration) to optimally participate in the wholesale electricity market. The optimal day-ahead bidding strategy of a large wind power producer to maximize its expected profit under uncertainties was studied in [12]. References [13, 14] numerically demonstrated the profitability of the coordinated scheduling of wind and thermal units participating in the wholesale electricity market compared to the nonintegrated one. Authors in [15] proposed a stochastic mixed-integer linear programming optimization model to determine the scheduling of a wind-thermal producer in the wholesale electricity market under the uncertainties of electricity price and wind power generation. Authors in [16] developed a coordinated bidding strategy for wind-hydro-pumped storage system to maximize the profit in the day-ahead and real-time balancing electricity markets. The work reported in [17] proposed a multiobjective framework to determine the optimal bidding strategy of a wind-thermal-energy storage system in the day-ahead electricity market. In this work, the presented optimization problem tries to simultaneously maximize the profit of coordinated energy sources and minimize the emission of GHG. The paper in [18] studied both price-maker roles in the day-ahead market and price-taker roles as balancing market in real time. Authors in [19] developed an optimization model to determine the optimal bidding strategy of a GENCO with coordinated wind-pumped storage-thermal system. The proposed model tries to maximize the economic profit of the GENCO participating in the day-ahead electricity and spinning reserve market, considering the wind generation uncertainty. The paper in [20] developed an intelligent programmed genetic algorithm (GA) equipped with advanced deterministic diversity creating operator to solve GENCO’s bidding strategy problem considering carbon credit trading. Reference [21] proposed a stochastic multiobjective bidding strategy model for participation of wind-thermal-photo-voltaic GENCO in the wholesale electricity market. Authors in [22] developed a coordinated bidding strategy model for participation of a combined energy system composed of wind farm and compressed air energy storage (CAES) in the day-ahead and ancillary service markets. The authors in [23] proposed a stochastic risk-constrained optimization problem to determine the bidding strategy of a GENCO owing wind-thermal-CAES system.

Although the above-reviewed studies have provided valuable insights into the coordinated bidding strategy of different energy sources, they have not considered the transmission network constraints. In this regard, a network-constrained linear programming model for the bidding strategy of a hydrothermal system was proposed in [24]. The uncertainties associated with market-clearing prices and forced outage of generators were considered in this work. Authors in [25] presented a multicriteria optimization problem to determine the bidding strategy of hydropower thermal systems. Herein, the uncertainty related to the load demand was modeled by scenario-based optimization. The paper in [26] proposed an optimization problem to determine the bidding strategy of a wind power producer with market power to participate in the day-ahead electricity market with the pay-as-bid payment mechanism. The paper only considered the uncertainty of wind power utilizing the scenario generation technique. A stochastic bilevel optimization problem was proposed for coordinated wind power and gas turbine systems in the real-time market regarding conditional value at risk (CVaR) [27]. Likewise, authors in [28] proposed a stochastic bilevel optimization model to determine the bidding strategy of a strategic wind power producer to participate in the network-constrained electricity market. The upper-level problem maximizes the economic benefit of the wind farm, and the lower-level problem clears the market based on the received bids of the market participants. A comprehensive stochastic optimal bidding strategy for a microgrid is proposed regarding the interdependency of power and gas market prices on the joint day-ahead and real-time markets [29]. In this paper, electricity market prices in the day-ahead and real-time markets, solar and wind productions, and the electrical and thermal demands were considered as uncertain parameters. In the above-reviewed studies, since the transmission network constraints were modeled using simple DC power flow equations, the constraints related to the voltage magnitude and the reactive power flowing in transmission lines have been ignored. Besides, the correlation between uncertain parameters is essential for optimal bidding strategy problems. However, the reviewed studies have not investigated the impact of correlation on the coordinated bidding strategy.

Contributions. As discussed in the literature review and to the best of the authors’ knowledge, the studies in the scope of coordinated bidding strategy have ignored the impact of AC power flow equations and correlation between uncertain parameters on the optimal bidding strategies. Complementary to the above-reviewed studies, this paper proposes a network-constrained bilevel bidding strategy model for a wind-thermal GENCO to maximize its profit. In the presented optimization problem, the uncertainties of wind power generation and electricity demand are modeled using a set of scenarios, considering their mutual correlation. Besides, the nonlinear constraints of AC power flow problem are reformulated as linear equations. Therefore, the significant contributions of the paper are briefed as follows:

A stochastic bilevel optimization problem is proposed to determine the coordinated bidding strategy of the wind-thermal system. In the upper-level problem, the
profit of GENCO in the day-ahead and the balancing market is maximized. On the other hand, the market-clearing optimization problem minimizes the total operation cost in the lower-level problem. It is worth mentioning that the Iberian Peninsula market mechanism is employed to model the revenue of the wind power producer.

The uncertain behaviors of wind output power and electricity demand are properly modeled in the optimization problem. Besides, the correlation of uncertain parameters is regarded in the model; that is to say, during a day in summer, when the wind speed increases, the ambient temperature will be decreased. Thus, consumers turn off their cooling systems, which will result in the electricity demand decrease. Consequently, wind turbines’ production power and electricity demand are negatively correlated. The proposed model’s mutual correlation between the uncertainties is modeled using the copula technique.

As stated earlier, relevant research works in the area of coordinated bidding strategy studies ignored either the transmission network constraints or employed simple DC power flow equations in the transmission network. To amend this shortcoming, the proposed model utilizes AC power flow equations. Besides, the nonlinear AC power flow constraints are linearized using the piecewise linear approximation technique to improve the accuracy of the solution and mitigate the computation time.

1.4. Paper Organization. The remainder of the paper is structured as follows. The main outlines of the proposed model, including uncertainty modeling and revenue function of the wind power producers in the Iberian Peninsula, are explained in Section 2. Section 3 provides the mathematical formulation of the proposed stochastic bilevel optimization problem and the solution methodology. The proposed coordinated bidding strategy model is implemented in the IEEE RTS 24-bus, and the effectiveness of the proposed model is discussed in Section 4. Finally, the conclusions are presented in Section 5.

2. Problem Description

This section will discuss the outlines of the developed optimal bidding strategy of the wind-thermal GENCO. First of all, the uncertainty modeling regarding the negative correlation between wind power and demand is presented. Then, the revenue function of the wind power producer in the Iberian Peninsula electricity market, including day-ahead and balancing market, is described.

2.1. Uncertainty Modeling. The wind-thermal system’s proposed coordinated bidding strategy model is exposed to the uncertainties of the wind output power and the electricity demand. As stated earlier, the uncertain parameters are highly correlated. For instance, during a day, when the wind speed increases (and therefore the wind output increases), some customers turn off their cooling systems, resulting in the electricity demand decrease. According to the historical data of Denmark wholesale electricity market [30] the wind speed and electricity demand in summer seasons are negatively correlated with the average correlation factor of −0.56. Note that the wind output power can be calculated using the nonlinear relation with the wind speed as (1). In this equation, $V_{ci}$, $V_{co}$, and $V_r$ are respectively cut-in, cut-out, and rated wind speed and parameters A, B, and C are calculated as follows [31–33].

$$p_w = \begin{cases} 
0, & 0 \leq V \leq V_{ci}, \\
(A + BV + CV^2)P_w^*, & V_{ci} \leq V \leq V_r, \\
P_w^*, & V_r \leq V \leq V_{co}, \\
0, & V \geq V_{co},
\end{cases}$$

(1)

$$A = \frac{1}{(V_{ci} - V_r)^2} \left[ V_{ci} (V_{ci} + V_r) - 4V_{ci}V_r \frac{(V_{ci} - V_r)^3}{2V_r} \right],$$

(2)

$$B = \frac{1}{(V_{ci} - V_r)^2} \left[ 4(V_{ci} + V_r) \frac{(V_{ci} - V_r)^3}{2V_r} - 3V_{ci} + V_r \right],$$

(3)

$$C = \frac{1}{(V_{ci} - V_r)^2} \left[ 2 - 4 \frac{(V_{ci} + V_r)^3}{2V_r} \right].$$

(4)

The copula technique is employed to properly consider the mutual correlation between the output power of the wind turbine and electricity demand [34]. The proposed approach determines the joint multivariate distribution according to the marginal cumulative distribution functions (CDF) [35]. Based on this technique, the joint multivariate distribution of random variables $(z_1, z_2, \ldots, z_n)$ can be presented as follows:

$$F(z_1, z_2, \ldots, z_n) = C(F_1(z_1), F_2(z_2), \ldots, F_n(z_n)),$$

(5)

where $F_i(z_i)$ is the marginal CDF of the random variable $z_i$ and $C(\cdot)$ represents the copula function. Thus, the joint multivariate distribution is calculated by means of the corresponding marginal CDFs and copula function. More detailed information on the technique can be found in [35]. Copula functions are mainly grouped into two categories: Elliptical copula and Archimedean copula [36]. Elliptical copula consists of Gaussian copula and t-copula, which can be used for symmetrical probability distribution functions (PDF). Archimedean copula includes Gumbel, Frank, and Clayton copulas suitable for asymmetrical PDFs and different tail correlations. The detailed information about these functions can be found in [37].

We utilized a scenario generation and reduction procedure to model the above-mentioned uncertainties. The
procedure employs the copula technique to model the correlation between prevailing uncertainties. Finally, the presented approach determines a set of scenarios for wind power and electricity demand fed into the optimization problem. The following procedure determines the final resulting scenarios.

1. Initialization:
   a. Consider the marginal PDFs for wind power and electricity demand
   b. Compute the marginal CDFs using the considered marginal PDFs

2. Copula function fitting:
   a. Consider a proper copula function
   b. Compute the parameters of copula function through marginal CDFs

3. Scenario generation and reduction technique:
   a. Select N random numbers within the range of [0, 1] for wind power and electricity demand using the copula function
   b. Compute the wind power and electricity demand using selected random numbers and inverse marginal CDFs
   c. The procedure continues until all scenarios are generated
   d. To mitigate the computational burden, the generated scenarios are reduced using the fast forward selection (FFS) technique [38]

2.2. Revenue Function of Wind Power Producer. The revenue of wind power producers in the electricity market consists of two terms: (i) revenue from selling energy in the day-ahead electricity market \( R_{DA} \) and (ii) revenue/penalty from participating in the real-time balancing electricity market \( R_{RT} \). Thus, the revenue of the wind farm is calculated as follows.

\[
R = R_{DA} + R_{RT}. \tag{6}
\]

The revenue from selling energy in the day-ahead electricity market can be calculated by multiplying the market-clearing price with the scheduled power (7). In the following equation, \( \lambda_t^{DA} \) and \( P_t^{ch} \) are the day-ahead market-clearing price and the scheduled power in the day-ahead electricity market, respectively.

\[
R_{DA} = \sum_{t \in T} \lambda_t^{DA} P_t^{ch}. \tag{7}
\]

Moreover, due to the uncertainty of wind speed, GENCO’s actual real-time wind power deviates from the scheduled power. Thus, GENCO must participate in the real-time balancing market to compensate for deviation. The revenue/penalty of GENCO for participating in the real-time balancing market can be calculated as follows:

1. When the actual wind power production is higher than the scheduled power and if there is an excess generation (system imbalance is positive), the wind turbine must sell the excess wind power production with a price less than or equal to day-ahead market-clearing price. Furthermore, if there is a deficit in generation (system imbalance is negative), the ISO tends to compensate for generation deficit with excess wind power production. The real-time balancing market price will equate the day-ahead market electricity price in this condition. Thus, the revenue of the wind power producer when the wind power generation is higher than the scheduled power is equal to

\[
R_{RT}^+ = (P_t^R - P_t^{ch}) \lambda_t^{RT}, \quad P_t^R > P_t^{ch}, \tag{8}
\]

where \([-\cdot-\cdot] \) represents the minimum operator, \( P_t^R \) is the actual real-time wind power production, \( \lambda_t^{RT} \) is the real-time balancing market price in the state of excess power production of the wind turbine, and \( \lambda_t^{DN} \) is the price that ISO purchases from wind turbine excess generation.

2. When the actual wind power production is lower than the scheduled power and if the system imbalance is positive, the ISO will sell the excess generation in the power system to the wind turbine owner with the price equal to the day-ahead market-clearing price. Moreover, if the system imbalance is negative, the wind turbine compensates for the power deficit with a price equal to or greater than the day-ahead market-clearing price. Thus, since the wind turbine will purchase the electricity in the real-time balancing market, the wind turbine revenue is negative, calculated as follows:

\[
R_{RT}^- = (P_t^R - P_t^{ch}) \lambda_t^{RT} - \ldots - P_t^R > P_t^{ch}, \tag{9}
\]

where \([\cdot\cdot\cdot\cdot\cdot\cdot] \) represents the maximum operator, \( \lambda_t^{RT} \) is the real-time balancing market price in the state of shortage wind power production, and \( \lambda_t^{UP} \) is the price that ISO receives to compensate for the shortcoming wind turbine generation [39].

3. Problem Formulation

Generally, the power generation units such as wind turbines can participate in the electricity market as price-taker and/or price-maker participants. In the former, the wind turbine submits zero price to the ISO, and consequently, the power production of the corresponding wind turbine will be purchased with the higher priority. In this condition, wind power production is modeled as the negative demand in the optimization problem. Although wind turbine modeling in the optimization problem is plain, it is not practical in a highly wind turbine penetrated system. In this study, the GENCO with wind turbine participates as the market maker participant in the wholesale electricity market. In this regard,
we deal with a bilevel optimization problem in which the first level determines the bid price-quantity of the GENCO by maximizing the profit. The market-clearing problem is solved in the second level to determine the market-clearing price and the generation units’ scheduling. Figure 1 illustrates the structure of the proposed bilevel optimization problem.

The mathematical formulation of the proposed stochastic bilevel bidding strategy model of the wind-thermal GENCO is presented as follows:

Maximize $Y_j = \sum_{s \in S} \sum_{t \in T} \pi_s Y_{j,s,t},$ 

$Y_{j,s,t} = \begin{cases} \text{LMP}_{j,s,t} P_{j,t} - c_j P_{\text{conv}}_{j,s,t} + \text{LMP}_{j,s,t}^r (P_{j,s,t} - P_{j,t}), & P_{j,t} \geq P_{j,s,t}, \forall t \in T, s \in S, \\ \text{LMP}_{j,s,t} P_{j,t} - c_j P_{\text{conv}}_{j,s,t} + \text{LMP}_{j,s,t}^l (P_{j,s,t} - P_{j,t}), & P_{j,t} < P_{j,s,t}, \forall t \in T, s \in S, \end{cases}$ 

$\text{LMP}_{j,s,t}^r = \max\{\text{LMP}_{j,s,t}, \text{LMP}_{j,s,t}^0\}, \forall t \in T, s \in S,$ 

$\text{LMP}_{j,s,t}^l = \max\{\text{LMP}_{j,s,t}^l, \text{LMP}_{j,s,t}^\text{DN}\}, \forall t \in T, s \in S,$ 

Minimize $\sum_{i \in I} \left( f_{i,t} P_{i,t} + f_{j,t} P_{j,t} \right),$ 

$f_{j,t}^{\min} \leq f_{j,t} \leq f_{j,t}^{\max},$ for $i \neq j$: $f_{i,t} = c_i \forall t \in T, i \in I,$ 

$p_{i,t}^{\min} \leq p_{j,t} \leq p_{i,t}^{\max},$ $p_j^{\min} \leq p_{i,t} \leq p_j^{\max}, \forall i \in I,$ 

$P_{b,s,t} - PD_{b,s,t} - \sum_{l \in (0 \cup b)} P_{l,s,t} = 0, \forall b \in B, t \in T, s \in S,$ 

$Q_{b,s,t} - QD_{b,s,t} - \sum_{l \in (0 \cup b)} Q_{l,s,t} = 0, \forall b \in B, t \in T, s \in S,$ 

$P_{l,s,t} = G_a V_{o(l),s,t} V_{o(l),s,t} V_{r(l),s,t} \cos(\theta_{o(l),s,t} - \theta_{r(l),s,t}) \right) 

- B_t V_{o(l),s,t} V_{r(l),s,t} \sin(\theta_{o(l),s,t} - \theta_{r(l),s,t}), \forall l \in L, t \in T, s \in S,$ 

$Q_{l,s,t} = -B_t V_{o(l),s,t} V_{r(l),s,t} \cos(\theta_{o(l),s,t} - \theta_{r(l),s,t}) 

- G_t V_{o(l),s,t} V_{r(l),s,t} \sin(\theta_{o(l),s,t} - \theta_{r(l),s,t}), \forall l \in L, t \in T, s \in S,$ 

$\left( P_{l,s,t} \right)^2 + \left( Q_{l,s,t} \right)^2 \leq S_{l,s,t}^{\max}, \forall l \in L, t \in T, s \in S,$ 

$V_{\min} \leq V_{b,s,t} \leq V_{\max}, \forall b \in B, t \in T, s \in S.$
Bid price-quantity

Upper level Problem
(Maximizing profit of wind-thermal GenCo)

Market clearing price and generation units' scheduling

Lower level Problem
(Market clearing problem)

Figure 1: Structure of the proposed bilevel optimization problem.

the active and reactive power generated by GENCOs installed at bus b in scenario s at time step t $P_{l,s,t}$ and $Q_{l,s,t}$ are the active and reactive power flows through line $l$ in scenario $s$ at time step $t$ that are calculated as (19) and (20). In these equations, $G_l$ and $B_l$ are respectively the conductance and susceptance of line $l$ and $V_{o(l),s,t}$ and $V_{r(l),s,t}$ are the voltage magnitude of sending and receiving buses of line $l$ in scenario $s$ at time step $t$. Similarly, $\theta_{o(l),s,t}$ and $\theta_{r(l),s,t}$ represent the voltage angle of sending and receiving buses. Finally, (21) and (22) impose the limitation of power passing through line $l$ and voltage magnitude of bus $b$.

The mathematical formulation of the lower-level problem (market-clearing problem) excluding constraints (19)–(21) forms a linear optimization problem. To enhance the accuracy of the solution and burden of the computational complexity, the nonlinear equations of the problem are linearized using the piecewise linear approximation technique [40]. According to the linearization technique, (19) and (20) are replaced by (23) and (24).

\[
P_{l,s,t} = G_l(V_{o(l),s,t} - V_{r(l),s,t} - \omega_{l,s,t} + 1) - B_l(\theta_{o(l),s,t} - \theta_{r(l),s,t}), \quad \forall l \in L, t \in T, s \in S,
\]
\[
Q_{l,s,t} = -B_l(V_{o(l),s,t} - V_{r(l),s,t} - \omega_{l,s,t} + 1) - G_l(\theta_{o(l),s,t} - \theta_{r(l),s,t}), \quad \forall l \in L, t \in T, s \in S.
\]

Considering the voltage range, \(|\theta_{o(l),s,t} - \theta_{r(l),s,t}| < 40^\circ\), $\omega_{l,s,t} = \cos(\theta_{o(l),s,t} - \theta_{r(l),s,t})$ represents the piecewise linear approximation; that is
\[
\omega_{l,s,t} = d_{l,s,t,k}(\theta_{o(l),s,t} - \theta_{r(l),s,t}) + h_{l,s,t,k}, \quad \forall l \in L, t \in T, s \in S,
\]
\[
\alpha^p_k P_{l,s,t} + \alpha^q_k Q_{l,s,t} \leq \alpha^r S_{l}^{\text{emax}}, \quad (k = 1, 2, \ldots, n_k) \forall l \in L, t \in T, s \in S.
\]

In the above equation, $n_k$ is the number of segments, and $\alpha^p_k$, $\alpha^q_k$, and $\alpha^r$ are linearization coefficients, calculated as follows:
\[
\alpha^p_k = \sin\left(\frac{2\pi k}{n_k}\right) - \sin\left(\frac{2\pi (k-1)}{n_k}\right),
\]
\[
\alpha^q_k = -\cos\left(\frac{2\pi k}{n_k}\right) - \cos\left(\frac{2\pi (k-1)}{n_k}\right),
\]
\[
\alpha^r = \sin\left(\frac{2\pi}{n_k}\right).
\]

After linearizing the lower-level problem, the described stochastic bilevel optimization problem is solved using the GA. Figure 2 shows the flowchart of determining the optimal bid price-quantity of the wind-thermal GENCO. As shown, the GA is executed after generating the scenarios of uncertain parameters. The algorithm generates the first population, and then the objective function is evaluated. The iterative procedure would continue until convergence is achieved.

4. Simulation Results

This section presents numerical results of the proposed model on the IEEE RTS 24-bus test system, as shown in Figure 3. The test system includes (i) 32 generation units with a capacity of 12–400 MW, (ii) 43 branches (38 transmission lines and 8 power transformers), and (iii) 17 load points. Besides, a wind farm with an installed capacity of 500 MW is considered in bus 14. The data associated with the test system can be found in [44]. In order to model the uncertainties of wind power and electricity demand, the historical data of Denmark’s electricity grid are utilized [30]. Table 1 shows the hourly correlation factor between uncorrelated variables, and generation units’ scheduling.
Input data

Generate wind speed and demand scenarios with total $N$ scenarios

Generate the first population of wind-thermal GenCo bid

$n = 1$

Clear the day-ahead market for scenario number $n$

$n = n + 1$

Calculate the profit of wind-thermal GenCo

$\text{Convergence satisfied?}$

Yes $\rightarrow$ Final Solution

No $\rightarrow$

Produce next generation

Calculate the expected profit of GenCo

$n < N$

Yes $\rightarrow$

$n = n + 1$

No $\rightarrow$

Figure 2: Flowchart of the proposed bidding strategy model for wind-thermal GENCO.

Figure 3: IEEE RTS 24-bus with a wind-thermal GENCO in bus 14.

Table 1: Hourly correlation factor between wind speed and demand uncertainties.

| Hour | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 |
|------|----|----|----|----|----|----|----|----|----|----|----|----|
| CF   | -0.3 | -0.3 | -0.3 | -0.3 | -0.4 | -0.4 | -0.5 | -0.5 | -0.5 | -0.6 | -0.6 |
| Hour | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| CF   | -0.6 | -0.6 | -0.6 | -0.5 | -0.5 | -0.5 | -0.5 | -0.5 | -0.4 | -0.4 | -0.4 | -0.4 |
the negative correlation between the power generation of the wind farm and the electricity demand can be perceived.

The methodology proposed in the study has been implemented in the MATLAB software on a PC with an Intel Core i7 processor (2.2 GHz) and 8 GB RAM. As explained in the above section, although the lower-level problem is linear, the upper-level problem has nonlinearity. Thus, to solve the presented nonlinear bilevel optimization problem, we utilized the GA method with proper input data. Although some guidelines for choosing population size and iteration number can be found in [45, 46], the literature does not offer a comprehensive method for this purpose. This paper utilizes the empirical values (population size of 200 and iteration number of 150). In the simulation study, to explore the impact of the thermal unit on the revenue of GENCO with wind production, two cases are considered: (i) a GENCO with 500 MW wind farm without the participation of thermal unit and (ii) a GENCO with 500 MW wind farm with the participation of an 80 MW thermal unit.

As the first step of the simulation study, the running time of the presented optimization problem is calculated. The average running time of the optimization problem considering the linearized AC OPF equations is 232 seconds, while the running time of the nonlinear optimization problem is 712 seconds. Thus, the presented linearization procedure efficiently mitigates the problem’s computational complexity. In the following simulation study, the effectiveness of the proposed coordinated bidding strategy in increasing the profit of GENCO and decreasing the risk of uncertainties is investigated. In this

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**Figure 4:** Expected wind power production and electricity demand.

**Figure 5:** The optimal bid price of GENCO.
regard, the optimal bid price and the expected LMP of both cases are illustrated in Figures 5 and 6. As can be seen, GENCO submits bid prices with higher value in the peak-demand hours 9–20 compared to off-peak hours. Besides, the results demonstrate that in case (ii), the GENCO submits the higher value of bid price to ISO with the thermal unit’s participation, consequently increasing the LMP of bus 14. The reason is stemmed from the supporting role of the thermal unit in the coordinated bidding strategy of the wind-thermal GENCO.

Moreover, the actual wind power production of the cases is depicted in Figure 7. The results illustrate that the wind farm sells more power (accordingly lower wind curtailment) in case (ii) compared to case (i). In other words, the corresponding wind farm in cases (i) and (ii) produce 4207 MWh and 4547 MWh with the revenue of $4980 and $13240, respectively. Furthermore, Figure 8 shows the power generation of the thermal unit in the day-ahead electricity market. Herein, the thermal unit generates higher active power in the peak-demand hours due to the higher value of LMP. Moreover, the thermal unit increases the active power generation to provide the extra demand and play as a supporting role in the bidding strategy of the wind-thermal GENCO. Therefore, the
profit of GENCO with and without the participation of thermal units is $14561 and $4980, respectively. To conclude, the proposed coordinated bidding strategy triples the profit of the wind-thermal GENCO compared to wind-based GENCO.

The hourly profit of GENCO in both cases is illustrated in Figure 9. As can be seen, the participation of the thermal unit increases the profit of GENCO during all hours of the day. Additionally, the outcome signifies that the profit of GENCO during early morning hours, in which the demand and LMP are low, would be negative as a result of penalizing GENCO in the real-time balancing electricity market. On the contrary, the hourly profit of GENCO would be positive in peak hours since the LMP is high.

Last of all, the influence of mutual correlation between prevailing uncertain parameters on the profit of the wind-thermal GENCO is examined. In this regard, a sensitivity analysis is performed on GENCO’s profit with/without regarding the correlation. Figure 10 illustrates the hourly profit of the wind-thermal GENCO. As shown in the figure, the appropriate modeling of correlation between uncertain parameters would increase the profit of the wind-thermal GENCO. Furthermore, the total daily profit of GENCO in four cases, i.e., with and without the participation of thermal unit and with and without consideration of the correlation between uncertainties, is tabulated in Table 2. The table shows that considering the correlation of uncertainties increases the profit of wind-thermal GENCO and wind GENCO by 35.2% and 19.6%, respectively.
5. Conclusion

This paper proposed a stochastic bilevel coordinated bidding strategy of a wind-thermal GENCO considering the copula-based correlation of wind power production and electricity demand uncertainties. At the upper level, the GENCO submitted the hourly bid price-quantity to the ISO, intending to maximize the profit. The electricity market was cleared at the lower-level based on the market participants’ bids and offers, considering linearized AC power flow equations. Finally, the proposed model was applied to the IEEE RTS 24-bus, and the numerical results illustrated the effectiveness of the proposed coordinated bidding strategy. According to the analysis on the computational efficiency, linearizing the AC power flow equations decreased the running time of the optimization problem by 67.4%, while the differences between the voltage magnitude in all buses and profit of wind-thermal GENCO in linearized and nonlinear AC power flow approaches were negligible. Moreover, the simulation results showed that since the participation of the thermal unit with wind farm has decreased the risk of uncertainties, the wind-thermal GENCO submitted a greater bid price, generated higher wind power, and consequently received higher LMP. Thus, the thermal unit in the supporting role for wind farm would increase the profit of wind-thermal GENCO by 35.2%.

Nomenclature

Sets and Indices
- $T$: Set of time intervals, indexed by $t$
- $S$: Set of scenarios, indexed by $s$
- $I$: Set of thermal GENCOs, indexed by $i$
- $B$: Set of buses, indexed by $b$
- $L$: Set of transmission lines, indexed by $l$
- $o(l), r(l)$: Indices of sending/receiving buses of line $l$

Parameters and Constants
- $\pi_s$: Probability of scenario $s$
- $P_{j,s,t}$: Available active power of GENCO $j$ at time step $t$ and scenario $s$ (MW)
- $c_j$: Incremental cost of GENCO $j$ ($$/\text{MWh}$)
- $f_{i,t}$: Bid price of thermal GENCO $i$ at time step $t$ ($$/\text{MWh}$)
- $f_{j,t}$: Bid price of wind-thermal GENCO $j$ at time step $t$ ($$/\text{MWh}$)
- $P_{\text{min}}^i$: Minimum power of thermal GENCO $I$ (MW)
- $P_{\text{max}}^i$: Maximum power of thermal GENCO $I$ (MW)
- $P_{\text{min}}^j$: Minimum power of wind-thermal GENCO $j$ (MW)
- $P_{\text{max}}^j$: Maximum power of wind-thermal GENCO $j$ (MW)
- $P_{D,b,s,t}$: Active load in bus $b$ at time step $t$ and scenario $s$ (MW)
- $Q_{D,b,s,t}$: Reactive load in bus $b$ at time step $t$ and scenario $s$ (MVAR)
- $G_l, B_l$: Conductance and susceptance of transmission line $l$
- $S_{\text{max}}^l$: Maximum power flow in transmission line $l$ (S)
- $V_{\text{min}}^l$: Minimum allowable range of voltage magnitude (V)
- $V_{\text{max}}^l$: Maximum allowable range of voltage magnitude (V)

Table 2: Total daily profit of GENCO in four cases.

| Cases                         | With considering correlation | Without considering correlation |
|-------------------------------|-----------------------------|--------------------------------|
| Total profit ($)              | Wind-thermal 14561          | Wind 4980                      |
|                               | Wind-thermal 10762          | Wind 4163                      |

Figure 10: Hourly profit of GENCO with and without considering the correlation.
Variables

$$Y_{j,s,t}$$: Profit of wind-thermal GENCO $j$ at time step $t$ in scenario $s$ ($\$$)

$$\text{LMP}_{j,s,t}$$: Locational marginal price of the bus of GENCO $j$ at time step $t$ in scenario $s$ ($\$/MWh$)

$$\text{LMP}^+_{j,s,t}$$: Real-time balancing market price in the state of excess wind power production of GENCO $j$ ($\$/MWh$)

$$\text{LMP}^-_{j,s,t}$$: Real-time balancing market price in the state of shortage wind power production of GENCO $j$ ($\$/MWh$)

$$p_{\text{conv.},j,s,t}$$: Active power production of thermal unit of GENCO $j$ at time step $t$ in scenario $s$ (MW)

$$P_{j,t}$$: Active power production of wind-thermal GENCO $j$ at time step $t$ (MW)

$$P_{i,t}$$: Active power production of thermal GENCO $i$ at time step $t$ (MW)

$$P_{b,s,t}$$: Active power generation in bus $b$ at time step $t$ and scenario $s$ (MW)

$$Q_{b,s,t}$$: Reactive power generation in bus $b$ at time step $t$ and scenario $s$ (MVAR)

$$P_{l,s,t}$$: Active power flowing in transmission line $l$ at time step $t$ and scenario $s$ (MW)

$$Q_{l,s,t}$$: Reactive power flowing in transmission line $l$ at time step $t$ and scenario $s$ (MVAR)

$$V_{b,s,t}$$: Voltage magnitude of bus $b$ at time step $t$ and scenario $s$ (V)

$$\theta_{b,s,t}$$: Voltage angle of bus $b$ at time step $t$ and scenario $s$ (rad).

Data Availability

Data are available upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] V. Amir, M. Azimian, and A. S. Razavizadeh, “Reliability-constrained optimal design of multicarrier microgrid,” *International Transactions on Electrical Energy Systems*, vol. 29, Article ID e12131, 2019.

[2] R. Habibifar, H. Saber, M. R. K. Gharigh, and M. Ehsan, “Planning framework for BESSs in microgrids (MGs) using linearized AC power flow approach,” in *Proceedings of the 2018 Smart Grid Conference (SGC)*, pp. 1–7, Sanandaj, Iran, November 2018.

[3] M. Azimian, V. Amir, and S. Javadi, “Economic and environmental policy analysis for emission-neutral multi-carrier microgrid deployment,” *Applied Energy*, vol. 277, Article ID 115609, 2020.

[4] Z. Xiao, “Energy management model of marine biomass energy industry based on supply and demand adjustment,” *Journal of Coastal Research*, vol. 103, no. sp1, pp. 1002–1005, 2020.

[5] E. T. Sayed, T. Wilberforce, K. Elsaid et al., “A critical review on environmental impacts of renewable energy systems and mitigation strategies: wind, hydro, biomass and geothermal,” *Science of the Total Environment*, vol. 766, Article ID 144505, 2020.

[6] S. Fan, Y. Wang, S. Cao, T. Sun, and P. Liu, “A novel method for analyzing the effect of dust accumulation on energy efficiency loss in photovoltaic (PV) system,” *Inside Energy*, vol. 236, Article ID 21112, 2021.

[7] T. Cai, M. Dong, H. Liu, and S. Nojavan, “Integration of hydrogen storage system and wind generation in power systems under demand response program: a novel p-robust stochastic programming,” *International Journal of Hydrogen Energy*, vol. 41, 2021.

[8] R. Tähmasebifar, M. P. Moghaddam, M. K. Sheikh-El-Eslami, and R. Kheirollahi, “A new hybrid model for point and probabilistic forecasting of wind power,” *Inside Energy*, vol. 211, Article ID 119016, 2020.

[9] H. Saber, M. Moemi-Aghtaie, and M. Ehsan, “Developing a multi-objective framework for expansion planning studies of distributed energy storage systems (DESSs),” *Energy*, vol. 157, 2018.

[10] A. Arya, S. Sisodia, S. Mehroliya, and C. S. Rajeshwari, “A novel approach to optimize bidding strategy for restructured power market using game theory,” in *Proceedings of the 2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*, pp. 1–6, Gunupur Odisha, India, December 2020.

[11] R. Habibifar, A. Aris Lekvan, and M. Ehsan, “A risk-constrained decision support tool for EV aggregators participating in energy and frequency regulation markets,” *Electric Power Systems Research*, vol. 185, Article ID 106367, 2020.

[12] S. Li and C. S. Park, “Wind power bidding strategy in the short-term electricity market,” *Energy Economics*, vol. 75, pp. 336–344, 2018.

[13] M. S. Al-Swaidti, A. T. Al-Awami, and M. W. Khalid, “Co-optimized trading of wind-thermal-pumped storage system in energy and regulation markets,” *Inside Energy*, vol. 138, pp. 991–1005, 2017.

[14] F. Peng, S. Hu, X. Fan et al., “Sequential coalition formation for wind-thermal combined bidding,” *Inside Energy*, vol. 236, Article ID 21475, 2021.

[15] R. Haiata, H. M. I. Pousinho, R. Melico, and V. M. F. Mendes, “Bidding strategy of wind-thermal energy producers,” *Renewable Energy*, vol. 99, pp. 673–681, 2016.

[16] M. Afshari Igder, T. Niknam, and M. H. Khooban, “Bidding strategies of the joint wind, hydro, and pumped-storage in generation company using novel improved clonal selection optimisation algorithm,” *IET Science, Measurement & Technology*, vol. 11, no. 8, pp. 991–1000, 2017.

[17] H. Khaledi, A. Abdollahi, M. Shafie-Khah et al., “Coordinated wind-thermal-energy storage offering strategy in energy and spinning reserve markets using a multi-stage model,” *Applied Energy*, vol. 259, Article ID 114168, 2020.

[18] S. Darvishi, G. Sheisi, and J. Aghaei, “Bidding strategy of hybrid power plant in day-ahead market as price maker through robust optimization,” *International Transactions on Electrical Energy Systems*, vol. 30, Article ID e12426, 2020.

[19] M. E. Nazari and M. M. Ardehali, “Optimal bidding strategy for a GENCO in day-ahead energy and spinning reserve markets with considerations for coordinated wind-pumped storage-thermal system and CO$_2$ emission,” *Energy Strategy Reviews*, vol. 26, Article ID 100405, 2019.

[20] D. Shah and S. Chatterjee, “Optimal GENCO’s bidding strategy in a power exchange facilitating combined power and emission trading using intelligent programmed genetic
algorithm," International Transactions on Electrical Energy Systems, vol. 30, Article ID e12463, 2020.

[21] H. Khaloie, A. Abdollahi, M. Shafee-Khah et al., "Co-optimized bidding strategy of an integrated wind-thermal-photo-voltaic system in deregulated electricity market under uncertainties," Journal of Cleaner Production, vol. 242, Article ID 118434, 2020.

[22] M. Aldaadi, F. Al-Ismail, A. T. Al-Awami, and A. Muqbel, "A coordinated bidding model for wind plant and compressed air energy storage systems in the energy and ancillary service markets using a distributionally robust optimization approach," IEEE Access, vol. 9, pp. 148599–148610, 2021.

[23] E. Akbari, R.-A. Hooshmand, M. Gholipour, and M. Parastegari, "Stochastic programming-based optimal bidding of compressed air energy storage with wind and thermal generation units in energy and reserve markets," Inside Energy, vol. 171, pp. 535–546, 2019.

[24] A. Esmaeily, A. Ahmadi, F. Raeisi, M. R. Ahmadi, A. Esmaeel Nezhad, and M. Janghorbani, "Evaluating the effectiveness of mixed-integer linear programming for day-ahead hydro-thermal self-scheduling considering price uncertainty and forced out age rate," Inside Energy, vol. 122, pp. 182–193, 2017.

[25] M. Simab, M. S. Javadi, and A. E. Nezhad, "Multi-objective programming of pumped-hydro-thermal scheduling problem using normal boundary intersection and VIKOR," Inside Energy, vol. 143, pp. 854–866, 2018.

[26] K. Afshar, S. F. Ghiasvand, and N. Bigdeli, "Optimal bidding strategy of wind power producers in pay-as-bid power markets," Renewable Energy, vol. 127, pp. 575–586, 2018.

[27] M. Rayati, H. Goodarzi, and A. Ranjbar, "Optimal bidding strategy of coordinated wind power and gas turbine units in real-time market using conditional value at risk," International Transactions on Electrical Energy Systems, vol. 29, no. 1, Article ID e2645, 2019.

[28] T. Dai and W. Qiao, "Optimal bidding strategy of a strategic wind power producer in the short-term market," IEEE Transactions on Sustainable Energy, vol. 6, no. 3, pp. 707–719, 2015.

[29] S. Haddadipour, V. Amir, and S. Javadi, "Strategic bidding of a multi-carrier microgrid in energy market," IET Renewable Power Generation, vol. 16, 2021.

[30] D. Yeom and P. La Roche, "Investigation on the cooling performance of a green roof with a radiant cooling system," Energy and Buildings, vol. 149, pp. 26–37, 2017.

[31] M. Azimian, V. Amir, S. Javadi, P. Siano, and H. H. Alhelou, "Enabling demand response for optimal deployment of multi-carrier microgrids incorporating incentives," IET Renewable Power Generation, vol. 16, 2021.

[32] H. Saber, M. Moenini-Aghaie, M. Ehsan, and M. Fotuhi-Firuzabad, "A scenario-based planning framework for energy storage systems with the main goal of mitigating wind curtailment issue," International Journal of Electrical Power & Energy Systems, vol. 104, pp. 414–422, 2019.

[33] X. Jin, Y. Chen, L. Wang, H. Han, and P. Chen, "Failure prediction, monitoring and diagnosis methods for slewing bearings of large-scale wind turbine: a review," Measurement, vol. 172, Article ID 108855, 2021.

[34] R. Ghorani, F. Pourahmadi, M. Moenini-Aghaie, M. Fotuhi-Firuzabad, and M. Shahidehpour, "Risk-based networked-constrained unit commitment considering correlated power system uncertainties," IEEE Transactions on Smart Grid, vol. 11, pp. 1781–1791, 2019.

[35] Y. Wang, N. Zhang, C. Kang, M. Miao, R. Shi, and Q. Xia, "An efficient approach to power system uncertainty analysis with high-dimensional dependencies," IEEE Transactions on Power Systems, vol. 33, pp. 2984–2994, 2017.

[36] R. B. Nelsen, An Introduction to Copulas, Springer Science & Business Media, Berlin, Germany, 2007.

[37] Y. Wang and Y. Luo, "Research of wind power correlation with three different data types based on mixed copula," IEEE Access, vol. 6, pp. 77986–77995, 2018.

[38] H. Heitsch and W. Römisch, "Scenario reduction algorithms in stochastic programming," Computational Optimization and Applications, vol. 24, no. 2, pp. 187–206, 2003.

[39] J. M. Morales, A. J. Conejo, K. Liu, and J. Zhong, "Pricing electricity in pools with wind producers," IEEE Transactions on Power Systems, vol. 27, no. 3, pp. 1366–1376, 2012.

[40] R. Habibifar, H. Ranjbar, M. Shafee-Khah, M. Ehsan, and J. P. Catalá, "Network-constrained optimal scheduling of multi-carrier residential energy systems: a chance-constrained approach," IEEE Access, vol. 9, 2021.

[41] H. Saber, M. Ehsan, M. Moenini-Aghtaie, M. Fotuhi-Firuzabad, and M. Lehtonen, "Network-constrained transactive coordination for plug-in electric vehicles participation in real-time retail electricity markets," IEEE Transactions on Sustainable Energy, vol. 12, pp. 1439–1448, 2020.

[42] C. Coffrin and P. Van Hentenryck, "Transmission system restoration with co-optimization of repairs, load pickups, and generation dispatch," International Journal of Electrical Power & Energy Systems, vol. 72, pp. 144–154, 2015.

[43] H. Saber, H. Mazaheri, H. Ranjbar, M. Moenini-Aghtaie, and M. Lehtonen, "Utilization of in-pipe hydropower renewable energy technology and energy storage systems in mountainous distribution networks," Renewable Energy, vol. 172, pp. 789–801, 2021.

[44] C. Grigg, P. Wong, P. Albrecht et al., "The IEEE reliability test system-1996. a report prepared by the reliability test system task force of the application of probability methods sub-committee," IEEE Transactions on Power Systems, vol. 14, no. 3, pp. 1010–1020, 1999.

[45] A. E. Eiben and S. K. Smit, "Parameter tuning for configuring and analyzing evolutionary algorithms," Swarm and Evolutionary Computation, vol. 1, no. 1, pp. 19–31, 2011.

[46] S. G. B. Rylander and B. Gotshall, "Optimal population size and the genetic algorithm," Population, vol. 100, p. 900, 2002.