



Bidding strategy for wind generation considering conventional generation and transmission constraints

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Abstract Under the environmental crisis of global warming, more efforts are put in application of low carbon energy, especially low-carbon electricity. Development of wind generation is one potential solution to provide low-carbon electricity source. This paper researches operation of wind generation in a de-regulated power market. It develops bidding models under two schemes for variable wind generation to analyze the competition among generation companies (GENCOs) considering transmission constraints. The proposed method employs the supply function equilibrium (SFE) for modeling the bidding strategy of GENCOs. The bidding process is solved as a bi-level optimization problem. In the upper level, the profit of an individual GENCO is maximized; while in the lower level, the market clearing process of the independent system operator (ISO) is modeled to minimize the production cost. An intelligent search based on genetic algorithm and Monte Carlo simulation (MCS) is applied to obtain the solution. The PJM five-bus system and the IEEE 118-bus system are used for numerical studies. The results show when wind GENCOs play as strategic bidders to set the price, they can make significant profit uplifts as opposed to playing as a price taker, because the profit gain will outweigh the cost to cover wind uncertainty and reliability issues. However, this may result in an increase in total production cost and the profit of other units, which means consumers need to pay more. Thus, it is necessary to

update the existing market architecture and structure considering these pros and cons in order to maintain a healthy competitive market.

Keywords Low carbon, Electricity market, Game theory, Generator bidding, Intermittency, Locational marginal pricing

1 Introduction

For almost half century, global warming is always one of many top challenges to human beings all over the world. many efforts have been made to in order to avoid disasters resulting from global warming, such as polar iceberg melting, sea level increasing, coast area recession, environment deterioration and extremely abnormal climate etc. One important milestone is the conclusion of “Kyoto Protocol” under collaborative efforts of international community in 1997 [1]. Particularly, carbon dioxide is widely believed as one of greenhouse gas and its greenhouse effect was confirmed by lots of experiments. Therefore, it is natural to advocate massive application of low-carbon energy in electricity sector, such as wind, solar, and hydro generation etc., in practice to alleviate carbon emission. Especially wind generation is quickly developing in quantity and still has huge potential to increase its total capacity. Recently, there are several studies about future prospect and possible challenge of developing low-carbon electricity [2–6].

Over the past decades, the old vertically structured power industry throughout the world has been gradually redesigned for market de-regulation [7]. The generation and transmission systems have been split into different entities to introduce competition into the power market. The purpose is to increase investment efficiency and to reduce the cost of power supply [8].

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A variety of market operation models have been proposed and practiced in various countries. Among all different models, the power pool market structure is the most popular one [8–14]. This power pool is managed by a market operator or an independent system operator (ISO) to collect the bids of energy suppliers from generation companies (GENCOs) and the offers of load consumers from load serving entities (LSEs). Then, a market clearing price (MCP) is calculated as the bid price of the most expensive supplier that is needed to completely meet the demand [10]. This market structure is built to encourage suppliers to bid their energy price close to their marginal cost to ensure economic efficiency. Further, to address the transmission constraints, an economic dispatch model is applied to minimize total generation supply cost while satisfying the system reliability and security requirements. Then, the locational marginal pricing (LMP) method [15] is usually employed to calculate the generation profit and load payment and to manage the transmission constraints.

Therefore, to model the dispatch function of the ISO and the individual behavior of the GENCO, it is naturally to split the bidding process into two parts [10–12]. The first part is the ISO market clearing process: the ISO collects all necessary information such as bids and offers from GENCOs and LSEs, and then performs security constrained economic dispatch (SCED) to set the market price. The second step is the self-scheduling of the GENCO for their own payoff optimization such that they can present the best bidding strategy in the forthcoming market.

Modeling and solving bidding strategies problem has been a hot research topic for a long time. In [9], a probability based Monte Carlo (MC) method is proposed to solve competitive generator game with imperfect information, but without transmission constraints. In [10], a mathematical analysis based on a Lagrangian Relaxation is proposed. In [16], a cooperative game is analyzed with potential coalitions and collusions of participants in electricity markets. A prime-dual interior point iteration based on sensitivity was developed to update bidding strategies for GENCOs in [11]. Bidding with transmission constraint was solved in [11–13]. Also in [12], it is shown that the feasibility of Bender Decomposition to solve bidding strategy problems in two parts. In [11], an incomplete information case combined with transmission constraint was carried out. A bidding strategy problem was solved by Monte Carlo simulation and genetic algorithm (GA) in [17]. Intelligent heuristic search such as GA is also a good way to deal with bidding strategy problems in [17, 18]. Further, for a multi-Nash equilibrium of multiplayer games in electricity markets, all Nash equilibria, if exist, could be calculated based on solving polynomial equations in [19]. An analytical approach of transmission-constrained residual demand derivative is used for a power market bidding problem solution in [20].

Strategies for wind power trading were studied in [21]. Two types of bid scenarios are proposed as linear bid and block bid trading for wind power generation, but the model did not consider transmission constraints and competition with other types of generators. In [22, 23], a trading strategy is given for wind power producers to minimize their imbalance cost in short-term, but the transmission constraints as well as competition with other types of generators are not considered. In [24], the uncertainty of wind power generation was modeled in constraints of an optimization problem instead of in the objective function. However, it did not consider the wind power generation as a variable in the objective function of the optimization problem.

The goal of this paper is to develop a bidding strategy model for wind generation participating in the competition with conventional generators. Here, the difference between two types of generators is the high uncertainty of wind generation. Thus, probabilistic approach is taken for the bidding strategy model. Also, the transmission constraints are considered. To solve the overall problem, a bi-level optimization model is formulated where the upper-level subproblem maximizes the payoffs of the GENCOs and the lower-level subproblem solves the market clearing problem of the ISO including economic dispatch and pricing. The Monte Carlo simulation (MCS) method is used to describe the wind generation statistical characteristic, linear programming (LP) is used to solve the lower-level subproblem, and GA is used to solve the upper-level subproblem.

The paper is organized as follows. Section 2 presents the problem formulation including the proposed wind generation bidding strategy model. Section 3 discusses the GA, a simplified Monte Carlo method and their applications to the solution of the proposed problem formulation. Section 4 shows the numerical examples with the PJM 5-bus system and the IEEE 118-bus system. Section 5 concludes the discussion.

2 Problem formulation

In a complete information game, all players know the bidding strategy of other players and their payoff functions. Equilibrium is reached when no player can increase its payoff by unilaterally changing its strategy.

Some assumptions commonly employed in bidding strategy study are listed as follows:

- 1) Each GENCO has only one generator unit and bids a constant price for a single block for simplicity, while in practice a monotonically increasing multi-block bid model is commonly used.
- 2) GENCO uses supply function equilibrium (SFE) model.

- 3) Load is always inelastic and constant for simplicity because load's bids can be essentially modeled as negative generation if needed.
- 4) Power losses on transmission lines are neglected and the transmission limit is considered in this paper.
- 5) The LMPs in day-ahead market are the same as those in the real-time market.

2.1 GENCO's bidding strategy model

GENCOs cannot decide the price just by themselves. It is the ISO to clear the market and determine the price. However, GENCOs can affect the price via their bidding strategies. Hence, the whole bidding process is a bi-level optimization problem. The first level is that each GENCO maximizes its own profit, and the second level is a transmission constrained economic dispatch by ISO to minimize total production cost under all security constraints.

Suppose all conventional GENCOs have a convex quadratic production cost function as follows

$$C_i = C(G_i) = a_i G_i^2 + c_i G_i + d_i \quad (1)$$

The marginal cost is calculated as

$$\frac{dC_i}{dG_i} = 2a_i G_i + c_i \quad (2)$$

where a_i is the generation cost coefficients of conventional GENCO i (\$/MWh²), c_i is the marginal cost of conventional GENCO i (\$/MWh), $C_i = C(G_i)$ is the generation production cost function of conventional GENCO i (\$), d_i is the generation cost coefficients of conventional GENCO i (\$), G_i is the scheduled generation of conventional GENCO i (MWh).

It is a linear function of its scheduled generation G_i . Obviously, GENCOs can make their strategic bids by changing a_i and c_i . For simplicity, in this paper, only c_i will be changed and also let a_i equals to zero based on assumption at the beginning of this section. Therefore, each GENCO will submit generator bids to the ISO according to the following linear supply function for Generator i .

$$f_i = b_i \cdot \frac{\partial C_i}{\partial G_i} = b_i \cdot c_i \quad (3)$$

where b_i is the unknown bidding strategic coefficient variable of conventional GENCO i (it equals to 1 for non-strategic bidders), f_i is the bidding price of conventional GENCO i (\$/MWh).

All of the wind GENCO shares the same description as in (1), (2) and (3). The only difference is that we use the subscript j for wind GENCOs, while other GENCOs use the subscript i .

2.2 Market clearance model

Suppose the ISO uses a transmission constrained economic dispatch to clear the market after collecting all bids and to calculate the market price based on the locational marginal pricing (LMP) model. If the wind power generation output is taken as a deterministic variable, the classic general DCOPF dispatch model is given as follows:

$$\min \sum_{i=1}^H b_i \cdot c_i \cdot G_i + \sum_{j=H+1}^T b_j \cdot c_j \cdot G_j \quad (4)$$

subject to

$$\sum_{l=1}^n G_l = \sum_{l=1}^n D_l \quad (5)$$

$$G_{i\min} \leq G_i \leq G_{i\max}, G_{j\min} \leq G_j \leq G_{j\max} \quad (6)$$

$$\sum_{l=1}^n F_{k-l} \cdot (G_l - D_l) \leq L_k \quad \text{for } k = 1, 2, \dots, m \quad (7)$$

where D_l is the load demand at bus l (MWh), $G_{i\min}$ and $G_{i\max}$ are the minimum and maximum generation output of conventional GENCO i (MWh) respectively, G_l is the generation at bus l (MWh), F_{k-l} the generation shift factor to line k from bus l , L_k is the transmission limit of line k .

The control variables are b_i , b_j , G_i and G_j . The GENCO production cost is minimized in (4). Constraint (5) ensures the balance of supply and demand. Constraint (6) represents the generation capacity limit. Constraint (7) represents the transmission line constraints.

After the economic dispatch is solved, LMP at each bus l (i.e. M_l) can be calculated as follows [15]:

$$M_l = \lambda + \left(\sum_{k=1}^m \mu_k \cdot F_{k-l} \right) \quad (8)$$

where $-\lambda$ is the Lagrange multiplier of (5), and $-\mu_k$ the Lagrangian multiplier of (7). Note we take $-\lambda$ and $-\mu_k$ as the Lagrangian multipliers such that we have positive signs when calculating LMP as shown in (8).

Once the energy market is cleared by ISO, each GENCO i will be paid according to its LMP and its dispatched generation. The payoff function for the conventional GENCO i and the wind GENCO j is given by

$$Y_i = M_i \cdot G_i - c_i \cdot G_i \quad (9)$$

$$Y_j = M_j \cdot G_j - c_j \cdot G_j \quad (10)$$

where Y_i , Y_j is the profit (\$) of conventional GENCO i and wind GENCO j respectively.

2.3 Probabilistic model of wind generation output

Wind generation output at a specific time spot is usually uncertain and cannot be described as a deterministic variable, so it is broadly accepted to use a random variable, subject to a statistical distribution, to represent it [25]. However, it is difficult to determine the distribution type due to insufficient historical data. Since wind speed forecast error is usually considered normally distributed and the wind speed and wind generation output can be considered linearly correlation in a small region, the wind generation output is assumed to roughly follow normal distribution from the viewpoint of the day-ahead operation [26]. Thus, the wind generation output distribution is given by

$$G_j(t) \sim N(\mu_j(t), \sigma_j(t)^2) \quad (11)$$

$$\varphi(x) = \frac{1}{\sigma_j \sqrt{2\pi}} e^{-\frac{(x-\mu_j)^2}{2\sigma_j^2}} \quad (12)$$

$$\Phi(x) = \int_{-\infty}^x \varphi(u) du \quad (13)$$

where $\mu_j(t)$ is the mean value of $G_j(t)$, $\sigma_j(t)$ is the variance of $G_j(t)$, $\varphi(x)$ is the probability density function (PDF) of $G_j(t)$, $\Phi(x)$ is the cumulative density function (CDF) of $G_j(t)$.

2.4 Wind generation bidding schemes

From the perspective of the ISO, the increasing penetration of renewable energy such as wind and solar generation presents great challenges because of its intermittency and uncertainty. This makes it harder than conventional generation to be controlled in practice. For example, in [20], the wind generation is considered undispatchable and sampled in different scenarios. For each scenario, it is taken as a deterministic negative load in the power balance constraint rather than in the objective function of the economic dispatch program. The ISO runs security constrained economic dispatch to find the output of conventional GENCOs. Finally, the expectation will be taken to combine the results of all scenarios together. As a matter of fact, it suffices to consider wind generation as a zero production cost source. It means that the wind generation will always be dispatched first because it often has the lowest production cost in reality. And this also matches with current practical dispatch policy, i.e., to dispatch renewable energy in priority to meet the percentage of wind penetration in the renewable portfolio standards (RPS). This is probably a legitimate model when the wind generation penetration level in the grid is low and insignificant.

However, with an increasing penetration of wind generation integrated into the grid, the above simple treatment of wind generation as a negative load is likely neither feasible nor reasonable. Also, this treatment tends to discourage wind power suppliers producing more wind power or making more profits. Although the advantage of this dispatch scheme is its easy implementation in practice, this scheme also excludes wind generation as a bidder in electric power market. Therefore, in this paper, two schemes are modeled to consider wind GENCOs as constraints (always dispatched first and being price takers) and as strategic bidders, respectively.

2.4.1 Scheme 1: wind generation as constraint in dispatch

Suppose the mean and variance values can be assessed beforehand. The ISO may use its mean value and its bidding price to carry out economic dispatch. When wind generation is considered into this bidding model, it should have some important adjustment. First, since wind source is intermittent, it is hard to use only one deterministic scenario to represent its performance. We have to consider its probabilistic characteristics, i.e., its expectation and variance.

In this paper, a Monte Carlo simulation model, elaborated in the next section, is employed to model the randomness. Suppose we take S samples for wind generation output $G_j(t)$, and each sampled scenario s has a corresponding probability P_s and a corresponding wind generation output $G_{j,s}$ for wind GENCO j . Note that $\sum_s P_s = 1$ for probability and $\mu_j(t) = E(G_j(t)) = G_j$ based on the proposed assumption.

Based on the previous discussion, for each Monte Carlo scenario s , the economic dispatch scheme from ISO's perspective can be described mathematically as follows:

$$\min \sum_{i=1}^H b_{i,s} \cdot c_i \cdot G_{i,s} \quad (14)$$

subject to

$$\sum_{l=1}^n G_l = \sum_{l=1}^n D_l \quad (15)$$

$$G_{i\min} \leq G_{i,s} \leq G_{i\max} \quad (16)$$

$$\sum_{l=1}^n F_{k,l} \cdot (G_l - D_l) \leq L_k \quad \text{for } k = 1, 2, \dots, m \text{ and all } s \quad (17)$$

where $b_{i,s}$ is the unknown bidding strategic coefficient variable of conventional GENCO i in scenario s (it equals to 1 for non-strategic bidders), $G_{i,s}$ the scheduled generation of conventional GENCO i in scenario s (MWh).

The control variables are $b_{i,s}$ and $G_{i,s}$. The difference between (4) and (14) is that wind generation variables are removed in (14). In fact, wind power generation cost could be viewed as zero cost in this case. In addition, the wind generation capacity constraint is removed in (16), while (15) and (17) remains the same as (5) and (7). Also, $\sum_{l=1}^n D_l$ in (15) and (17) is the total load subtracts the total wind generation offset. After this transmission constrained economic dispatch process, the LMP calculation still follows (8) and the payoff function for conventional GENCO i and wind GENCO j is the same as (9) and (10), respectively. For each scenario s , the profit of conventional GENCO i is as follows:

$$Y_{i,s} = M_{i,s} \cdot G_{i,s} - c_i \cdot G_{i,s} \quad (18)$$

Since the wind GENCO j is a price-taker in this case, its profit function at scenario s is calculated as follows:

$$Y_{j,s} = M_{j,s} \cdot G_{j,s} - c_j \cdot G_{j,s} \quad (19)$$

where $Y_{i,s}$, $Y_{j,s}$ is the profit (\$) of conventional GENCO i or wind GENCO j in scenario s respectively.

Therefore, the whole bidding process can be rewritten as a bi-level optimization problem as follows:

$$\max_{i,s} Y_{i,s} = \max_{i,s} (M_{i,s} \cdot G_{i,s} - c_i \cdot G_{i,s}) \quad (20)$$

subject to

$$b_{i,\min} \leq b_{i,s} \leq b_{i,\max} \quad (21)$$

$$\min \sum_{i=1}^H b_{i,s} \cdot c_i \cdot G_{i,s} \quad (22)$$

subject to

$$\sum_{l=1}^n G_l = \sum_{l=1}^n D_l \quad (23)$$

$$G_{i,\min} \leq G_{i,s} \leq G_{i,\max} \quad (24)$$

$$\sum_{l=1}^n F_{k-1} \cdot (G_l - D_l) \leq L_k \quad \text{for } k = 1, 2, \dots, m \text{ and all } s \quad (25)$$

The control variables are $b_{i,s}$ and $G_{i,s}$. The objective function for a strategic bidder i at scenario s is given by (20). The first constraint (21) is to set a limitation with $b_{i,s}$ selection to be realistic; otherwise, the bidder can have infinite market power in theory.

Thus, the total profit expectation of conventional GENCO i for all scenarios is calculated as follows:

$$Y_i = E[Y_{i,s}] = \sum_s P_s \cdot Y_{i,s} \quad (26)$$

And the total profit expectation of wind GENCO j for all scenarios is calculated as follows:

$$Y_j = E[Y_{j,s}] = \sum_s P_s \cdot Y_{j,s} \quad (27)$$

2.4.2 Scheme II: wind generation as strategic bidder

In this scheme, the randomness of wind power is also modeled via Monte Carlo simulation. This is the same as in Scheme I.

The difference is that wind GENCOs are taken as strategic bidders in this scheme. Since wind generation is not a constant power source, its payoff function needs to be modified for each sampled scenario s as follows:

$$\begin{aligned} \text{a) } G_j > G_{j,s} \\ Y_{j,s} &= M_{j,s} \cdot G_{j,s} - c_j \cdot G_{j,s} \\ &\quad + M_{j,s} (G_{j,s} - G_j) \end{aligned} \quad (28)$$

$$\begin{aligned} \text{b) } G_j < G_{j,s} \\ Y_{j,s} &= M_{j,s} \cdot G_j - c_j \cdot G_{j,s} \\ &\quad + M_{j,s} (G_{j,s} - G_j) = M_{j,s} \cdot G_{j,s} - c_j \cdot G_{j,s} \end{aligned} \quad (29)$$

Next, the objective function in (28) and (29) is explained. After sampling, it is a deterministic process for each scenario. At the end of the market clearing process of the ISO, all LMPs and generation dispatches will be settled. The wind GENCO will get its revenue as shown by the first item on the left hand side of (28) and (29). The second item in (28) and (29) is its production cost.

The third item in (28) is the obligation penalty cost if it cannot meet the dispatch requirement in day-ahead market subject to its output uncertainty, because it has to purchase the gap amount of power from the real-time spot market. If it has more generation than required in day-ahead market as in (29), it is assumed to earn extra profits from selling it to the real-time spot market with the day-ahead price. This approach represents the penalty or extra profit due to insufficient or extra output in real-time. Since the goal of this paper is to compare the two schemes, as long as they are based on the same assumption (no price difference between day-ahead and real-time), the comparison is fair.

Therefore, the whole bidding process can be rewritten as a bi-level optimization problem shown below:

if it is a conventional GENCO

$$\max_i Y_i = \max_{i,s} (M_{i,s} \cdot G_{i,s} - c_i \cdot G_{i,s}) \quad (30)$$

or if it is a wind GENCO with $G_j > G_{j,s}$

$$\max_j Y_j = \max_{j,s} \left(M_{j,s} \cdot G_{j,s} - c_j \cdot G_{j,s} + M_{j,s} (G_{j,s} - G_j) \right) \quad (31)$$

or if it is a wind GENCO with $G_j < G_{j,s}$



$$\max_j Y_j = \max_{j,s} \begin{pmatrix} M_{j-s} \cdot G_{j-s} \\ -c_j \cdot G_{j-s} \end{pmatrix} \quad (32)$$

subject to

$$b_{i \min} \leq b_{i-s} \leq b_{i \max}, b_{j \min} \leq b_{j-s} \leq b_{j \max} \quad (33)$$

$$\min \sum_{i=1}^H b_{i-s} \cdot c_i \cdot G_{i-s} + \sum_{j=H+1}^T b_{j-s} \cdot c_j \cdot G_{j-s} \quad (34)$$

subject to

$$\sum_{l=1}^n G_l = \sum_{l=1}^n D_l \quad (35)$$

$$G_{i \min} \leq G_{i-s} \leq G_{i \max}, G_{j \min} \leq G_{j-s} \leq G_{j \max} \quad (36)$$

$$\sum_{l=1}^n F_{k-l} \cdot (G_l - D_l) \leq L_k \quad \text{for } k = 1, 2, \dots, m \text{ and all } s \quad (37)$$

The control variables are b_{i-s} , b_{j-s} , G_{i-s} and G_{j-s} . If it is a conventional GENCO, the upper level objective function is (30), while if it is a wind GENCO, the upper level objective function should be replaced as (31) and (32) instead. Again, (33) is to set a limitation with the b_{i-s} and b_{j-s} selections to avoid the bidder to have infinite market power in theory. In the lower level optimization, LMP calculation still follows (8) and the expected payoff function for conventional GENCO i and wind GENCO j follows (26) and (27) respectively.

Therefore, its final profit expectation of wind GENCO j for all wind generation output scenarios is considered as

$$\begin{aligned} a) G_j > G_{j-s} \\ Y_j &= E[Y_{j-s}] \\ &= \sum_s P_s \cdot \begin{bmatrix} M_{j-s} \cdot G_{j-s} - c_j \cdot G_{j-s} \\ + M_{j-s} (G_{j-s} - G_j) \end{bmatrix} \end{aligned} \quad (38)$$

$$\begin{aligned} b) G_j < G_{j-s} \\ Y_j &= E[Y_{j-s}] \\ &= \sum_s P_s \cdot [M_{j-s} \cdot G_{j-s} - c_j \cdot G_{j-s}] \end{aligned} \quad (39)$$

3 Monte Carlo simulation and genetic algorithm

3.1 Monte Carlo simulation

The Monte Carlo simulation, applicable to both Scheme I and II, is implemented as follows:

- 1) The PDFs of wind GENCOs are obtained as the inputs of the Monte Carlo simulation.

- 2) Take s repeated random samplings for the PDF of each wind GENCO j to obtain G_{j-s} and P_s for each Monte Carlo sampled scenario s .
- 3) For each scenario s , perform a deterministic optimization based on GA and then LP to calculate all bidding strategies, all GENCO costs, dispatches, all LMPs, and the profits for all GENCOs (conventional and wind).
- 4) Aggregate the results to get the profit expectation of all GENCOs.

The Monte Carlo simulation will stop when a pre-defined convergence threshold ε has been reached. The stopping criterion is shown mathematically as follows [27]:

$$\frac{\sigma[E(X)]}{E(X)} = \frac{\sigma(X)}{\sqrt{s} \cdot E(X)} \leq \varepsilon \quad (40)$$

where X is the random variable representing the wind generation profit, $E(X)$ the mean value of X , and $\sigma(X)$ the standard deviation of X .

3.2 GA

Essentially, this proposed optimization problem is to find the global Nash equilibrium to each bidder. The formation of the proposed solution is a bi-level optimization, which is depicted in Fig 1. There are various approaches to solve this non-linear, non-convex, bi-level optimization. Here the GA is used in this paper. Note that the term ‘biological generation’ instead of the commonly used term ‘generation’ in the GA algorithm discussion, is used to avoid possible confusion with the electrical generation.

Generally, the algorithm terminates when either a maximum number of generations is reached, or a satisfactory fitness level has been reached for the population. If the algorithm is terminated due to a maximum number of

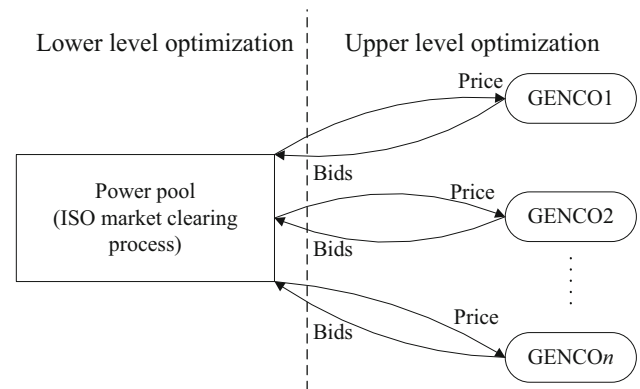


Fig. 1 Framework of the proposed bi-level GA optimization process

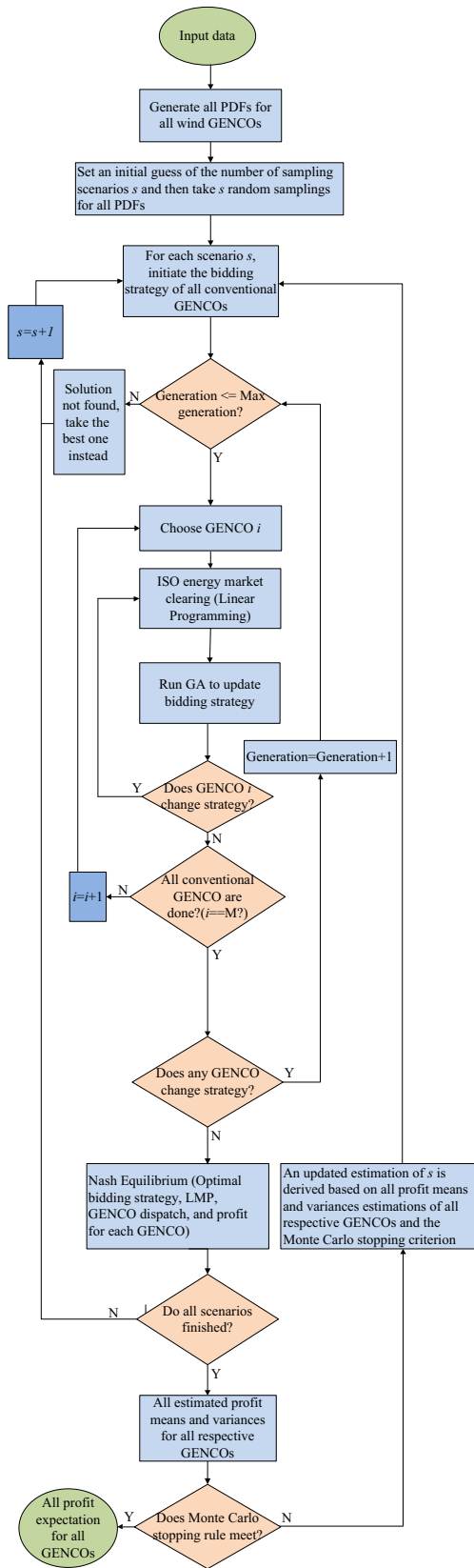


Fig. 2 Flowchart of the proposed GA and Monte Carlo simulation for wind generation bidding scheme I

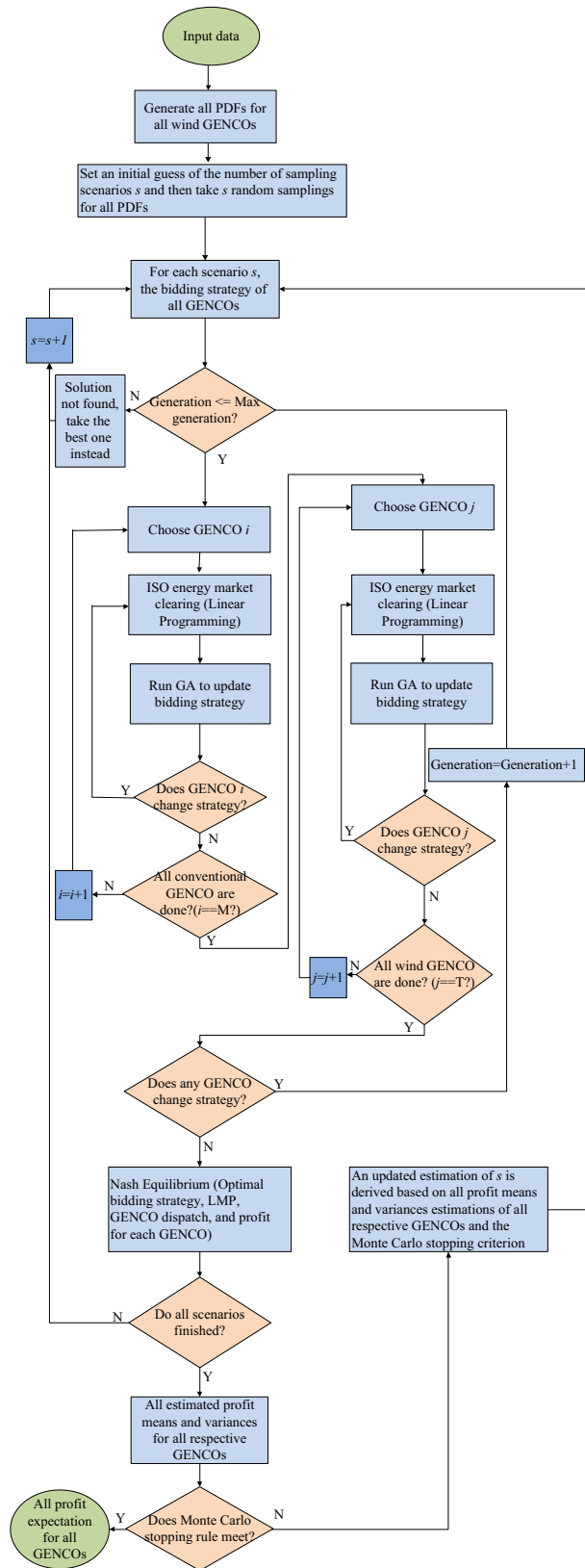


Fig. 3 Flowchart of the proposed GA and Monte Carlo simulation for wind generation bidding scheme II



generations, a satisfactory solution may or may not have been reached.

By combining the results of all scenarios based on Monte Carlo simulation and GA, the expected results can be derived. The flowcharts of Scheme I and II are shown in Figs. 2–3.

4 Numerical example analysis

The stopping criterion ε of Monte Carlo simulation is set to 0.01 for all cases below [27]. In addition, for the parameters associated with GA applied to the cases below, we set the total biological generation to 100, the population size to 50, crossover rate to 0.5, mutation rate to 0.01, and eight bits for bidding strategy coefficients (b_i and b_j). Also, the GA stopping criterion is that the relative difference between the previous profit and the current profit of each GENCO is less than 1% of the current profit for all scenarios in each case.

4.1 PJM five bus system

This modified PJM five-bus system is shown in Fig 4 [15]. The transmission line profiles are shown in Table 1. In the modified system, its total load level is 900 MW. Alta is a wind generator which observes normal distribution

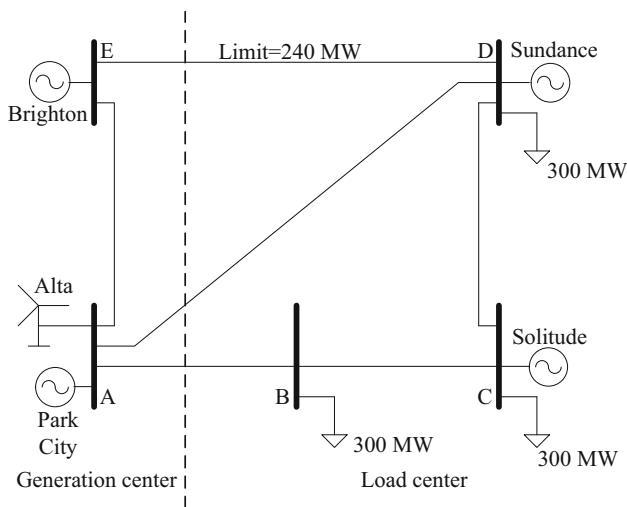


Fig. 4 Modified PJM five-bus system

Table 1 Line impedance and flow limit

Line	AB	AD	AE	BC	CD	DE
X (%)	2.81	3.04	0.64	1.08	2.97	2.97
Limit (MW)	999	999	999	999	999	240

Table 2 Generator data

Generator	Alta	Park City	Solitude	Sundance	Brighton
Type	Wind	Hydro	Gas	Gas	Steam
P_{\min} (MW)	50	0	0	0	10
P_{\max} (MW)	150	100	520	300	600
Marginal cost (\$/MWh)	7	15	30	35	10

with a mean output 100 MW and standard variance 16.67 MW. Considering the practical limit of wind output is three times of standard variance, the wind generation output will be within the interval [50 MW, 150 MW] with 99.7% confidence based on normal distribution. All other generators are conventional units, with unit minimum and maximum generation and cost listed in Table 2 according to the type of each generator.

4.1.1 Scheme I: wind generation as a constraint

Let Park City and Sundance be the two bidders involved within this case. The two bidding strategy coefficients for Park City and Sundance are constrained to be in interval [1, 3] and [1, 1.5], respectively. They may bid up to 45 \$/MWh and 52.5 \$/MWh, respectively. Therefore, they have a wider range to set the price.

Wind generation is considered to be a negative load in this scheme. 1000 sampling scenarios are taken in this case. The profit, generation and price expectation for each generator are shown in Table 3.

The GA convergence rate (i.e., ratio between number of scenarios converged to a Nash equilibrium and total scenarios) is 1. It means that the probability of reaching a Nash equilibrium solution under current system conditions is 100%. The average total generation cost of this scheme is \$12959.

4.1.2 Scheme II: wind generation as a bidder

All the assumptions and parameters are the same as in the previous case in Section 4.1.1. The only difference is

Table 3 Profit generation and price expectation for each generator

Generator	Alta	Park City	Solitude	Sundance	Brighton
Expected profit (\$)	1129	0	0	0	1664
Expected output (MW)	100	0	212.82	0	587.19
Expected price (\$/MWh)	18.78	18.78	30	38.56	12.77

Table 4 Profit and price expectation for each generator

Generator	Alta	Park City	Solitude	Sundance	Brighton
Expected profit (\$)	1893.8	0	0	0	9593.3
Expected output (MW)	69.84	0	238.28	0	591.77
Expected price (\$/MW)	27.39	27.39	30	31.99	25.99

that Alta is also a price bidder of the whole bidding process at this time with bidding strategic coefficient constrained in interval $[1, 5]$ such that the wind unit's bid can be up to 35 \$/MWh, which is in a comparable range of the bids of the other strategic units. Thus, there are three bidders in this case. The profit expectation is shown in Table 4.

The GA convergence rate in this case is 0.99, i.e. the probability of reaching a Nash equilibrium solution is 99% under the current system conditions. The average total generation cost of this system is \$13773, which is about 6.3% higher than the previous case in Section 4.1.1.

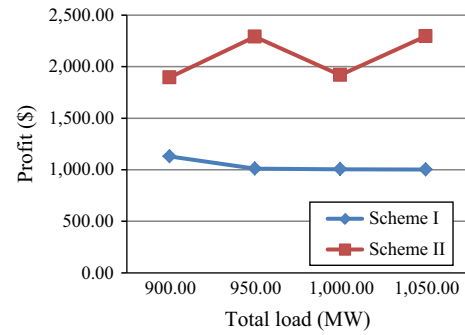
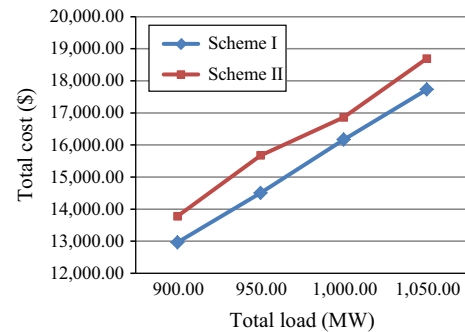
4.1.3 Analysis of results with sensitivity study

If we compare the results of the above two cases in Tables 3 and 4, we can conclude that the profit of wind generator Alta in the Scheme II is more than in the Scheme I case even with less expected generation because the profit gains weight much more than the possible losses when under-production occurs. This implies that allowing wind unit to bid may financially help them cover their own uncertainty and reliability issues. The profit of generator Solitude is 0, which means the LMP on this bus is always the same as its marginal cost in both cases. In addition, generator Park City and Sundance also earn no profit due to zero production.

However, the generator Brighton is the biggest winner in Scheme II, because the LMP at its bus doubles and its expected output stays the same. Also, the total generation cost goes up by 6.3% which is also significant. Thus, there are pros and cons for allowing wind generation to participate in bidding. This implies the need of an update in the power market architecture and structure for adapting high penetration of wind generation.

Based on different total system load levels, the sensitivity study is performed. The comparison of the profit of wind generator Alta and the total cost of the system are shown in the following figures.

As shown in Figs. 5–6, the load level increases in a 50 MW step. At different load levels, the wind generation bidder consistently earns in Scheme II more than in Scheme I, while the total system cost is in Scheme II higher

**Fig. 5** Comparison of the profit of wind generator Alta**Fig. 6** Comparison of the total cost of the system

than in Scheme I as well. At the studied four load levels, the GA always has a high convergence rate (i.e., ratio between the number of scenarios converged to a Nash equilibrium and the total number of scenarios) more than 99.5%, which guarantees the validity of the results.

When the total system load level goes beyond 1100 MW or even more, the convergence rate of GA is lower than 50%. This means the total generation capacity is not sufficient. Thus, the sensitivity analysis is stopped at 1050 MW load level.

4.2 IEEE 118-bus system

There are 186 branches, 91 loads, and 54 generators in the IEEE 118-bus test system. All the detailed information can be found in [28]. The original IEEE 118-bus system data does not contain the information of generator marginal costs and branch thermal limits. Therefore, generator marginal costs are constructed in this paper as follows: 2 wind generators with marginal cost \$8, 20 cheap generators with marginal cost from \$10 to \$19.5 with \$0.5 increment; 18 expensive generators with marginal cost from \$20 to \$23 and \$26 to \$39 with \$1 increment; and 14 extremely expensive generators with marginal cost from \$40 to \$53 with \$1 increment. In addition, five thermal limits are introduced into the transmission system: 345 MW for lines

69–77, 630 MW for lines 68–81, 106 MW for lines 83–85 and 94–100, 230 MW for lines 80–98 [26]. Also, the maximum total generation is more than twice of the total load. In order to show the efficiency of wind generation, each load is scaled up at 1.8 times of its original value in the whole system.

Suppose two wind GENCOs are located at buses 59 and 61, respectively. Their generation output mean values are 155 MW and 160 MW, respectively. Also, they have the same standard variance at 33.33 MW to make possible wind generation output in the interval [55 MW, 255 MW] and [60 MW, 260 MW], respectively, with 99.7% confidence based on the normal distribution property. In addition, the two wind generations are independent random variables each other. All other generators are conventional.

4.2.1 Scheme I: wind generation as a constraint

Let generators at buses 65, 66 and 69 be the strategic players involved in this case. The three bidding strategy coefficients are constrained to be in interval [1, 2] such that the involved units may bid up to \$56/MWh which gives a sufficiently wide range for the simulation.

Wind generation is considered to be a negative load in this scheme with 1000 sampling scenarios. The profit expectation is shown in Table 5. (Here only the results of the strategic bidders and wind generator owners are listed).

The GA convergence rate (i.e., ratio between the number of scenarios converged to a Nash equilibrium and the total number of scenarios) is 1, which means that the probability of finding a Nash equilibrium solution is 100% under the current system conditions. The average generation cost is \$176430.

Table 5 Profit expectation for each generator

Generator at bus	59	61	65	66	69
Expected profit (\$)	4577.4	4727.9	5354.8	4839.9	6981.7
Expected output (MW)	153.74	158.66	490.9	491	794.75
Expected price (\$/MW)	37.85	37.87	37.9	37.86	37.84

Table 6 Profit expectation for each generator

Generator at bus	59	61	65	66	69
Expected profit (\$)	4838.5	4952.5	5826.4	5328.9	7876.7
Expected output (MW)	108.04	115.36	491	491.51	801.91
Expected price (\$/MW)	38.84	38.85	38.87	38.84	38.83

4.2.2 Scheme II: wind generation as a bidder

All the assumptions and parameters are the same as in the previous case in 4.2.1. The only difference is that the two wind units at buses 59 and 61 are market players in the entire bidding process with the bidding factor in the range of interval [1, 6]. Thus, we will have five bidders in this case. Similar to the previous case in 4.2.1, 1000 sampling scenarios are taken. The profit expectations of five strategic bidders are shown in Table 6.

The GA convergence rate is 99.5%, which means the probability of having a Nash equilibrium solution is 99.5%. The average total generation cost is \$178080, which is about 1% increase from Scheme I. Since the five strategic bidders represent a small portion of the total units, this 1% increase is considerable.

4.2.3 Analysis of results

If we compare the results of these two cases in Table 5 and Table 6, the observation shall be very similar to the one from the previous PJM 5-bus system study. Both wind generation bidders may have tremendous profit uplift as a marginal unit even though the probabilistic uncertainty is considered, because the gains from wind strategic bidding outweigh the cost of purchasing power due to insufficient wind production. From this perspective, the renewable generation will be encouraged to aggressively play in the power market to gain more profits.

However, also similar to the PJM 5-bus case study, the above benefit is at the cost of increased total production cost and more profit of other conventional generation bidders. Thus, the consumers will pay more.

Therefore, this implies the power market architecture and structure should be updated to better accommodate high penetration of wind power. Also, the high GA convergence rate guarantees the validity of the results.

5 Conclusions

The contribution of this paper can be summarized as follows:

- 1) Two bidding strategy schemes are modeled in this paper to consider wind GENCOs, conventional GENCOs, and transmission constraints, while few literatures has studied the impact of wind GENCOs to bidding strategy. The first scheme considers wind power as negative loads, which is aligned with the ongoing practice that wind generation must be dispatched with higher priority. The second scheme regards wind GENCOs as possible strategic bidders,

which is aligned with the common expectation that wind power owners may participate in market competition in the future.

- 2) In each scheme, a comprehensive bidding strategy model is proposed in a probabilistic approach using Monte Carlo simulation. In each Monte Carlo sample, a bi-level optimization model is employed with different objective functions for wind GENCOs. The GA is employed as the solution method.
- 3) Simulation results show that, when wind GENCOs play as strategic bidders to set the price, they can make significant profit gains as opposed to playing as a price taker. Note this result considers the probabilistic variability of wind generation output. However, this is at the cost of increased production cost and the profit of other generators, which means the consumers will pay more. Thus, we can draw an important conclusion that when there is a high-penetration of wind generation, it is very necessary to update the existing market architecture in terms of competitive electricity market for high-penetration renewables.

The future work may include the bidding strategy model with ancillary service models, detailed penalty model and the effect of GENCO's collusion and coalition in the power electricity market.

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