Impact of renewable energy sources on modelling of bidding strategy in a competitive electricity market using improved whale optimization algorithm

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Abstract
In a competitive power market, generating utilities can be enhanced to achieve maximum profit by implementing a process of bidding strategy. Now-a-days renewable sources like solar and wind have become better alternatives significantly than other sources prior to power generation. These sources have extensive utilisation day-by-day in power sector and their impact in developing precise bidding strategies is getting more challenging aspect in the market. Since these renewable sources possess intermittent nature and undergo many uncertainties, the generating utilities encounter an unavoidable problem. Taking these aspects into consideration, attempts have been made using improved whale optimization algorithm to make the bidding strategy model for maximizing the power supplier's profit. Weibull and Beta distribution functions are used for modelling the stochastic characteristics of wind-speed profile and solar-irradiation, respectively. The proposed technique is tested and clarified with an IEEE-30, IEEE-57 and practical 75-bus Indian system. The outcomes of this method were taken into comparison with other optimization techniques and found that it has an advantage upon other methods in solving bidding problems. Further, it is observed that the impact of renewable sources on bidding strategy reduces the market clearing price and the generation of thermal power while increases the total bidding power.

1 INTRODUCTION

Now-a-days the electric industries are apparently going through restructuring and adopting the deregulated market strategy which creates competitiveness among the companies for power trading. In this competitive electricity market, risk minimization and profit maximization are more concerned by the electric industries. In order to attain high profit, strategic bidding has to be carried out by the electric utilities. The profit of power generating utilities and large buyers are truly dependent on marginal cost price (MCP). MCP plays a crucial act in this competitive energy market scenario. The supply and demand curves are taken for determining the value of MCP and this is decided by the SO. MCP follows the mechanism used in market clearing strategy for deciding the worth of consequent unit of power produced. Adopting this mechanism, a viable consequence is obtained to the optimal bidding problem. In today's power grid, sources from renewable energy like wind and solar become an inseparable part. Prior to power generation renewable energy sources becomes an alternative in comparison to other non-renewable sources. These renewable sources possess uncertain behaviour due to which many constraints arise in market for power trading.

The main objective of this context is to develop the bidding strategy model, considering a double sided bidding configuration for maximizing the profit of generating utilities and large buyers, in a deregulated environment. The impact of renewable sources on bidding model is analysed by modelling its uncertainties. The analysis is made for different test bus and practical bus system.

First, the optimal bidding problem was solved using dynamic programming approach for conventional power suppliers in
restructured power market environment [1, 2]. The concept of game theory and method of Nash equilibrium were applied to strategic bidding problem by authors in refs. [3, 4], respectively. After using classical methods for solving bidding problem, the authors in refs. [5–10] uses different optimization techniques considering the factors like cost of generations, market constraints and rival’s bidding behaviour that affect the bidding strategy problem. The risk issue is chosen as the key issues for bidding problem [11] where the risk is minimized for profit maximization in a competitive electricity market. In the above mentioned literatures the problem was solved for conventional power sources only.

Now-a-days, use of renewable sources has been growing very hastily. Due to its nature of uncertainty, it makes the bidding more challenging for the market players in deregulated energy market [12]. Modelling of uncertainties associated with the renewable sources have been analysed in ref. [13]. Authors in this paper modelled these sources considering different probability density functions (PDFs). During previous decades endeavours have been induced to resolve problems arising in the area of renewable sources in competitive market. The bidding problem is solved, aiming towards operating cost minimization by taking only wind source [14–17] and only solar source [18], into account. Likewise, multiple renewable sources such as battery storage system, PV system, wind and thermal systems have been considered in refs. [19, 20] for solving bidding problem, which emphasize only on demand side bidding to minimize large buyers payment. Whereas, for scheduling and dispatching of generating utilities [21, 22], the problem has been solved with the renewable sources by considering its overestimation and underestimation cost which are associated with the surplus or shortfall of renewable energy generation. In the above literatures authors have considered the uncertainties of renewable sources while modelling the bidding problem. However, it is not taken into consideration for solving the problem [23].

Apparently, literature study yields the various techniques of optimization which can be utilized for solving the bidding strategy problem, which maximizes the profit of suppliers. Few researchers have analysed the bidding strategy model while considering both generation and demand side utilities [24–29]. The efficacy of these heuristic optimized techniques is measured by tuning its parameter. The approaches where the parameters are less tuned provide high accuracy. In this concern, a novel Meta-heuristic approach known as whale optimization algorithm is introduced by Mirjalili and Lewis [30] which is based on hunting behavioural nature of whales and its application in formulating optimal strategic problem has been studied in ref. [31]. As the randomization plays a dynamic role in this approach so the process of searching is slow to get optimum value. Therefore to obtain better optimal solution that makes a balance between exploration and exploitation stage, an improved whale optimization algorithm (IWOA) is implemented in this paper by employing improvement factor and cosine control parameter. This improves the convergence rate and obtain a global optima rather than local optima.

So, to address the problems which were not attended earlier in the literatures, this paper attempts to implement an IWOA technique for maximizing the profit of generating utilities as well as of large buyers in competitive electricity market. The impact of renewable sources on bidding strategy problem has been done considering uncertainties associated with them. The uncertainties stochastic characteristics were modelled by using Beta PDF for solar source and Weibull PDF for wind source. The developed bidding strategy model using IWOA has been solved for different test systems consisting of IEEE-30, 57 bus system. It is apparent that the technique is relevant in this aspect and acceptable due to its efficacy while verifying with a practical 75-bus Indian system with and without renewable sources.

2 MATHEMATICAL MODELLING OF BIDDING STRATEGY

2.1 Determination of market clearing price

To enhance the profits of generating utilities and large buyers, appropriate trading strategy should be followed. However, the system may encounter risks, associated in obtaining an optimal trading strategy. In spite of this, system demand should be maintained with a definite end goal in order to clear the market using either with minimum price or maximum profit. Taking all these strategies into account in a power market, each supplier is meant to receive a single MCP and subsequently output of the generator is dispatched.

For proposed structure, Assume $I_i$, as the number of generating utilities involved in the restructured energy market, ‘$d_i$’, as the number of large consumers, interested in bidding on demand side. In this competitive market, every seller and buyer should bid on a linear non-diminishing supply function and non-expanding demand function.

The supply function and demand functions are considered as follows:

\[
X_m (P_m) = \alpha_m + (\beta_m \times P_m) \quad m = 1, 2, \ldots, d_i \quad (1)
\]

\[
Y_n (D_n) = a_n - (b_n \times D_n) \quad n = 1, 2, \ldots, d_i \quad (2)
\]

where $\alpha_m, \beta_m$ and $a_n, b_n$ are the bidding coefficients having positive value.

After getting the bid data from market utilities, system operator (SO) matches the total generation with total demand. Then it minimizes the cost of purchasing and maximizes the profit. In addition, it makes benefit of supplier and buyer for power dispatch considering different market constraints such as constraints of equality and inequality. The corresponding power market equality constraints [32] are given as follows:

\[
\alpha_m + (\beta_m \times P_m) = MCP, \quad (3)
\]

\[
a_n - (b_n \times D_n) = MCP, \quad (4)
\]

\[
\sum_{m=1}^{\xi} P_m + \sum_{m=1}^{\xi} P_{wg_m} + \sum_{m=1}^{\xi} P_{sw_m} = Q (MCP) + \sum_{m=1}^{d_i} D_n. \quad (5)
\]
The inequality constraints are given as follows:

\[
\begin{align*}
P^{\text{min}}_m & \leq P_m \leq P^{\text{max}}_m, \quad (6) \\
D^{\text{min}}_n & \leq D_n \leq D^{\text{max}}_n, \quad (7) \\
P^{\text{min}}_{\text{wind}} & \leq P_{\text{wind}} \leq P^{\text{max}}_{\text{wind}}, \quad (8) \\
P^{\text{min}}_{\text{solar}} & \leq P_{\text{solar}} \leq P^{\text{max}}_{\text{solar}}, \quad (9)
\end{align*}
\]

Equations (8) and (9) show generation limits of renewable energy sources. 

\(Q(MCP)\) represents load forecasted by pool, which is given as:

\[
Q(MCP) = C_0 - k \times MCP, \quad (10)
\]

where \(C_0\) represents load constant and \(k\) is elasticity factor of load.

The solutions to the Equations (3)–(5) without considering inequality constraints becomes,

\[
\begin{align*}
\text{MCP} &= \frac{C_0 - \sum_{w=1}^{\text{gen}} P_{\text{gen},w} - \sum_{n=1}^{\text{load}} P_{\text{load},n} + \sum_{l=1}^{\text{load}} \frac{\alpha_l}{\beta_l} + \sum_{s=1}^{\text{load}} \frac{\alpha_s}{\beta_s}}{k + \sum_{w=1}^{\text{gen}} \frac{1}{\beta_w} + \sum_{n=1}^{\text{load}} \frac{1}{\beta_n}}, \\
P_m &= \frac{\text{MCP} - \alpha_m}{\beta_m}, \quad (12) \\
D_n &= \frac{\text{MCP} - \alpha_n}{\beta_n}. \quad (13)
\end{align*}
\]

After obtaining value of MCP, if the solution violates its limit for Equations (12) and (13), then it must be brought to the specified limit as mention by Equations (6) and (7).

### 2.2 Maximization of profit

Profit maximization of power generating utilities can be obtained by performing optimal strategic bidding, which can be expressed as follows:

maximize profit \(G(\alpha_m, \beta_m) = \text{MCP} \times (P_m + P_{\text{wind},m} + P_{\text{solar},m}) - C_m(P_m) - C_m(P_{\text{wind},m}) - C_m(P_{\text{solar},m}). \quad (14)\)

Likewise, the profit of the buyer is expressed as follows:

\[
G(\alpha_m, \beta_m) = C_u(D_u) - \text{MCP} \times (D_u). \quad (15)
\]

The cost function of all power suppliers and buyers are given as follows:

i. thermal generating utilities,

\[
C_m(P_m) = (\epsilon_m \times P_m) + (f_m \times P_m^2). \quad (16)
\]

Here \(\epsilon_m\) and \(f_m\) are the cost coefficients of thermal generating utilities

ii. wind power generating utilities,

\[
C_w(P_{\text{wind},m}) = C_{U,m}(W_{\text{wind},avl} - W_{\text{pre}}) + C_{O,m}(W_{\text{avl}} - W_{\text{pre}}). \quad (17)
\]

The operating cost of \(w^{th}\) wind power generating utility consists of two parts that is underestimation and overestimation cost [21]. This underestimation and overestimation arise for wind source because of its sporadic nature.

Underestimation of wind power come into existence when power available from wind source is more than the predicted power of wind source and overestimation for wind source happens when power available from wind is less than the predicted power of wind source.

The Equation (17) consists of two terms whereas first term represents the penalty cost for underestimation and second term represents penalty cost for overestimation, which are given as follows:

\[
\begin{align*}
C_{U,m} \left( W_{\text{wind},avl} - W_{\text{pre}} \right) &= k_m \times \int_{W_{\text{pre}}}^{W_{\text{avl}}} f_m(w) \times dw \\
& \quad \times f_m(w) \times dw \quad (18) \\
C_{O,m} \left( W_{\text{pre}} - W_{\text{wind},avl} \right) &= k_m \times \int_0^{W_{\text{pre}}} \left( W_{\text{pre}} - W_{\text{avl}} \right) \times dw \\
& \quad \times f_m(w) \times dw \quad (19)
\end{align*}
\]

iii. solar power generating utilities,

\[
C_w(P_{\text{solar},m}) = C_{U,m}(S_{\text{solar},avl} - S_{\text{pre}}) + C_{O,m}(S_{\text{pre}} - S_{\text{solar},avl}). \quad (20)
\]

Similar to the wind power, the operating cost of solar power generating utility also have overestimation and underestimation due to the uncertainty nature of solar irradiance [22], which are given as follows:

\[
\begin{align*}
C_{U,m} \left( S_{\text{solar},avl} - S_{\text{pre}} \right) &= k_m \times \int_{S_{\text{pre}}}^{S_{\text{avl}}} \left( S_{\text{avl}} - S_{\text{pre}} \right) \times f_m(S) \times ds \\
& \quad \times f_m(S) \times ds \quad (21)
\end{align*}
\]
\[ C_{O,m} (S_{pre} - S_{m,av}) = k_{oc} \times \int_{0}^{S_{pre}} (S_{pre} - S_{m,av}) \times f_s (S) \times ds \]  

(22)

\[ C_a (D_a) = (g_a \times D_a) - (b_a \times D_a^2). \]  

(23)

where \( g_a \) and \( b_a \) are the cost coefficients of larger buyers.

To maximize the profit of supplier as well as buyer, it must require determining the bidding coefficients \((\alpha_m, \beta_m)\) or \((a_a, b_a)\) correspondingly by satisfying given market power constraints.

### 2.3 Probabilistic strategy

In competitive power market, generating utilities submit sealed bid to SO. Hence it becomes difficult for collecting the information of offers required for consequent bidding and solving the maximization problem. However, considering past bidding information [32], which are available to all market utilities, the assessment of bidding coefficients for rival can be established by using joint normal distribution PDF.

For \( m^{th} \) generating utility, the PDF is defined as,

\[
\text{PDF} (\alpha_m, \beta_m) = \frac{1}{2\pi \sigma_m^2 \sigma_m^2 \sqrt{1 - \rho_m}} \exp \left[ \frac{-1}{2 (1 - \rho_m^2)} \left\{ \left( \frac{\alpha_m - \mu_m}{\sigma_m} \right)^2 + \left( \frac{\beta_m - \mu_m}{\sigma_m} \right)^2 \right\} \right].
\]  

(24)

In matrix form, the PDF is represented as,

\[
(\alpha_m, \beta_m) = K \begin{bmatrix} \mu_m^a & \sigma_m^2 & \rho_m \sigma_m^2 \\ \mu_m^b & \sigma_m^2 & \rho_m \sigma_m^2 \\ \end{bmatrix} \begin{bmatrix} \alpha_m \\ \beta_m \\ \end{bmatrix}.
\]  

(25)

Similarly, for \( n^{th} \) large consumer, the PDF in matrix form is defined as,

\[
(a_a, b_a) = K \begin{bmatrix} \mu_a^c \\ \mu_a^b \\ \end{bmatrix} \begin{bmatrix} \sigma_a^2 \\ \rho_a \sigma_a^2 \\ \sigma_a^2 \\ \end{bmatrix} \begin{bmatrix} \alpha_a \\ \beta_a \\ \end{bmatrix},
\]  

(26)

where,

\[
\rho_m \text{ and } \rho_a \text{ represents the coefficient of correlation between } (\alpha_m \text{ and } \beta_m) \text{ and } (a_a \text{ and } b_a).
\]

\[ \mu \text{ and } \sigma \text{ represents the mean standard deviation respectively.} \]

### 3 MODELLING OF RENEWABLE ENERGY SOURCES

#### 3.1 Model for wind speed and power estimation

To characterise the speed profile of wind, Weibull distribution function [33] is chosen as the most convenient probability distribution function, which is given as

\[
f_w (V) = \frac{a}{b} \left( \frac{V}{b} \right)^{(a-1)} \times \exp \left( -\left( \frac{V}{b} \right)^{a} \right).
\]  

(27)

For \( a > 0, b > 1, 0 < V < \infty \),

where, \( a \) and \( b \) are estimated using the mean and standard deviation of wind speed,

\[
a = \left( \frac{\bar{V}}{\mu} \right)^{-0.086} \quad \text{is the shape parameter and}
\]

\[
b = \frac{\mu}{\Gamma(1+\frac{1}{a})} \quad \text{is the scale parameter.}
\]

The estimation of output of wind power is derived from wind speed profile and can be expressed mathematically [30] as:

\[
W_v = \begin{cases} 
0 & \text{if } v < v_{in} \\
\frac{w_r (v - v_{in})}{v_r - v_{in}} & v_{in} < v < v_r \\
w_r & v_r < v < v_o \\
0 & \text{if } v > v_o 
\end{cases}
\]  

(28)

When the speed range lies between \( v_{in} \) and \( v_r \), the distribution function for wind power output follows a continuous probability and its PDF becomes,

\[
F_w (W) = \frac{\alpha}{\mu} \left( \frac{1 + \frac{w}{\alpha w}}{b} \right)^{(\alpha-1)} \exp \left[ -\left( \frac{1 + \frac{w}{\alpha w}}{b} \right)^{\alpha} \right],
\]  

(29)

where

\[
\alpha = \frac{v_r - v_{in}}{v_{in}}.
\]

And for speed range between \((v < v_{in})\), \((v > v_r)\) and \((v_{in} < v < v_r)\) the distribution function of wind power follows a discrete probability and its PDF is expressed as,

\[
F_w (W) = \begin{cases} 
-\left( \frac{v_r}{b} \right)^{\alpha} & \text{if } v_{in} < v < v_r \\
-\left( \frac{v}{b} \right)^{\alpha} & \text{if } v < v_{in} \\
-\left( \frac{v}{b} \right)^{\alpha} & \text{if } v > v_r
\end{cases}
\]  

(30)
\[ F_w(W) \leq W_{\text{min}} \rightarrow 1 - \exp \left[ -\frac{h_w}{b} \right]^d + \exp \left[ -\frac{h_w}{b} \right]^d. \] (31)

### 3.2 Model for solar irradiance and power estimation

To model the solar irradiation, beta distribution function [33] is chosen as the most convenient PDF, which is expressed as,

\[ f_s(S) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} S^{(\alpha - 1)} (1 - S)^{-(\beta - 1)}. \] (32)

For \( 0 \leq S \leq 1 \) and \( \alpha, \beta > 0 \)

where,

\[ f_s \] is the beta distribution function and \( S \) is a random variable.

\( \alpha, \beta \), are the shape parameters which are estimated by using mean and standard deviation of solar data as follows:

\[ \alpha = \frac{\mu_s \beta}{1 - \mu_s}, \]

\[ \beta = (1 - \mu_s) \left[ \frac{\mu_s (1 + \mu_s)}{\sigma_s^2} - 1 \right]. \]

Considering a solar PV panel, the total output power of solar cell is calculated using the ambient temperature and specified radiation level as,

\[ P_o = \int_0^1 P_o(S) f_s(S) \, ds \] (33)

\[ P_o(S) = N \times FF \times V_{PV} I_{PV}. \] (34)

From the \( V-I \) characteristics of solar PV panel, it can be obtained that,

\[ FF = \frac{V_{mP} f_m}{V_{oc} I_{sc}}, \] (35)

\[ V_{PV} = V_{oc} - t_v T_{PV}, \] (36)

\[ T_{PV} = T_A + S \left( \frac{T_N - 20}{0.8} \right), \] (37)

\[ I_{PV} = S \left[ I_{sc} + t_v (T_{PV} - 25) \right]. \] (38)

The total output power of solar PV panel follows beta distribution, which is given by,

\[ F_s(P_o) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} (P_o)_{(\alpha - 1)} (1 - P_o)_{(\beta - 1)}. \] (39)

### 3.3 Characterisation of uncertainty of wind and solar

Wind and solar power generating sources have stochastic behaviour as discussed earlier and this behaviour comprises of many random variables. This intermittent characterisation was done by creating a number of scenarios which are nothing but the consequences of the random inputs, with equivalent probability of occurrence. Auto-regressive moving average (ARMA) model based on statistical time series is utilised to generate the scenarios. From the generated scenarios, output power can be obtained using power curve. For accuracy, 1000 numbers of scenarios are generated here. But due to time limit and complexity in calculation, reduction of scenarios is required which shows the predictable power produced by utilities. This scenario reduction is performed by using Kantorovich distance matrix [34], which is based on the probability distance between the scenarios. Probability distance is nothing but the vector distance among two scenarios due to which it is viable to obtain a scenario very close to original from the reduced scenarios. After scenario reduction the power generated by the sources are given as follows:

\[ P_{wg} = \sum_{i=1}^{N_s} P_{wi} \times P_{ri}, \] (40)

\[ P_{sg} = \sum_{i=1}^{N_s} P_{si} \times P_{ri}. \] (41)

### 4 WHALE OPTIMIZATION ALGORITHM (WOA)

For optimizing different numerical problems S. Mirjalili [30] proposed whale optimization algorithm (WOA), which is enthused from the hunting behavioural nature of humpback whales. This behaviour tells about how these whales trap small school of fishes, called as krill. This foraging hunting behaviour follows the strategy of bubble net feeding. During strategy of feeding, these whales create bubbles in a spiral shaped path, move upward direction following the bubbles, and trap the small fishes. This mechanism acts as a key factor for performing WOA.

The processes used for WOA are: (a) encircling process for the prey, (b) process for bubble net strategy, and (c) searching process for the prey.

#### 4.1 Encircling process for the prey

The humpback whales after finding their place for hunting encircle the prey. The current position or the optimum point of the best candidate is considered as main target and the position of the other candidates will be updated following the current
4.2.2 Spiral updating process

The movement of humpback whales in spiral shaped path is done in WOA by using the following equations,

\[ \vec{M} (t + 1) = \vec{M}^* (t) - \vec{A} \vec{P}, \quad (43) \]

where, \( \vec{P} \) gives the space among whale and the corresponding prey and \( t \) shows the current iteration. \( \vec{M}^* \) and \( \vec{M} \) are the vectors representing the position of best solution and position of each search agents, respectively. \( \vec{A} \) and \( \vec{G} \) are the vector coefficients calculated as,

\[ \vec{A} = 2 \vec{a} \vec{n} - \vec{a}, \quad (44) \]

\[ \vec{G} = 2 \mu \vec{n}, \quad (45) \]

where \( \vec{n} \) is an arbitrary number that lies between \([0, 1]\), \( \vec{a} \) is a control parameter that decreases linearly from 2 to 0 over the process of iteration.

4.2.3 Searching process for the prey

The process of searching used for tracing the prey is considered as the exploration phase in WOA. Here, the value of \( \vec{A} \) is chosen either greater than 1 or less than \(-1\). The mathematical equation governing this process is as follows:

\[ \vec{P} = \vec{G} \cdot \vec{M}_{\text{rand}} - \vec{K}, \quad (49) \]

\[ \vec{M} (t + 1) = \vec{M}_{\text{rand}} - \vec{A} \vec{P}, \quad (50) \]

where, \( \vec{M}_{\text{rand}} \) is a random number.

In Equation (50), the performance of WOA is affected significantly by the selection of parameter.

Here, when \( |\vec{A}| > 1 \), it gives importance to exploration phase where search agent is chosen randomly and when, \( |\vec{A}| < 1 \) the search agent, that is the best, is chosen for revising the position of search particle.

5 | IMPROVED WOA

At the starting stage of WOA, the target prey is chosen as the best search agent and other search agents updated their position following the present position of target prey as per the Equations (42) and (43). It is obvious that, at the starting stage the best search agent acquires an unknown position, due to which we are unable get the solution of optimum point. Therefore, to obtain the optimal solution and to make a balance between the exploitation and exploration stage, two improvement factors [35] and a control parameter [36] are employed in original WOA, respectively. Control parameter is represented by cosine function, expressed as below:

\[ \vec{a} = (a_{\text{max}} - a_{\text{min}}) \times \cos \left( \frac{\mu t}{\text{iter}_{\text{max}}} \pi \right), \quad (51) \]

where, \( a_{\text{max}} \) and \( a_{\text{min}} \) are maximum and minimum value of \( \vec{a} \), \( \mu \) and \( t \) are the adjust factor and current iteration, respectively.

After the implication of improvement factors \( F_1 \) and \( F_2 \) in the exploration and exploitation stage the modified equations are:

\[ \vec{P} = \left[ \frac{\vec{G} \vec{M}^* (t) - \vec{K} (t)}{F_1} \right], \quad (52) \]

\[ \vec{K} (t + 1) = \left[ \frac{\vec{K}^* (t) - \vec{A} \vec{P}}{F_1} \right], \quad (53) \]

and the update position in the spiral shape path becomes

\[ \vec{K} (t + 1) = \left[ \frac{\vec{D} \cos (2\pi t) + \vec{K}^* (t)}{F_2} \right]. \quad (54) \]

The position obtained using Equations (49) and (50) of WOA leads to random movement of whales. Due to which in IWOA,
TABLE 1 Standard deviation (S. D.) and average obtained by IWOA for unimodal benchmark functions in contrast with other algorithms

|   | IWOA | WOA   | PSO   | GSA   | DE    |
|---|------|-------|-------|-------|-------|
| F | S. D. | Average | S. D. | Average | S. D. | Average | S. D. | Average | S. D. | Average | S. D. | Average |
| F1 | 0.35003 | 28.259  | 7.63626 | 27.86558 | 60.11559  | 96.718  | 62.22534  | 67.54309  | 0  | 0 |
| F2 | 0.2376 | 0.74162 | 0.532429 | 3.116266 | 8.20815 | 28.24105 | 8.945084 | 9.75417 | 0  | 0 |
| F3 | 0.19105 | 0.56954 | 0.266088 | 1.880015 | 8.90 × 10−3 | 6.67 × 10−3 | 7.1262 | 8.890084 | 4.8 × 10−14 | 5 × 10−14 |

TABLE 2 Standard deviation and average obtained by IWOA for multimodal benchmark functions in contrast with other algorithms

|   | IWOA | WOA   | PSO   | GSA   | DE    |
|---|------|-------|-------|-------|-------|
| F | S. D. | Average | S. D. | Average | S. D. | Average | S. D. | Average | S. D. | Average |
| F8 | 2859.9 | −5948.2 | 695.7968 | −5080.76 | 1152.814 | −4841.29 | 493.03 | −2821.07 | 574.7 | −11080.1 |
| F9 | 9.01 × 10−16 | 1.12 × 10−15 | 9.879572 | 7.4043 | 0.50901 | 0.276015 | 0.236 | 6.20815 | 4.2 × 10−08 | 9.7 × 10−08 |
| F10 | 0.025032 | 0.0481 | 0.214864 | 0.339676 | 2.63 × 10−2 | 6.91 × 10−3 | 0.951 | 1.799617 | 8 × 10−15 | 7.9 × 10−15 |
| F11 | 0.19105 | 0.56954 | 0.266088 | 1.880015 | 8.90 × 10−3 | 6.67 × 10−3 | 7.1262 | 8.890084 | 4.8 × 10−14 | 5 × 10−14 |

5.1 Performance evaluation of IWOA technique

To assess the enactment of the suggested IWOA, the optimization is carried out on standard benchmark test functions. Two types of benchmark function, that is, unimodal (F1-F7) and multimodal (F8-F13) were used for the analysis. Unimodal functions are known to be the ones having only one local minima whereas multimodal functions possess multiple minima. For the study of analysis the optimum solutions ($f_{\text{min}}$), ranges, dimensions (Dim) and expressions of the corresponding benchmark functions were adopted from [30]. The consequences of the suggested technique are contrasted with several metaheuristic algorithms such as WOA, PSO, GSA and DE. Table 1 describes the relation of average, deviation for unimodal functions; likewise, Table 2 provides the idea of standard deviation, average statistical parameters for multimodal functions. Figure 1 shows the pseudo code for the improved WOA approach. The performance is tested preferring 30 number of search agents and 500 number of iterations. The outcomes are obtained doing 30 independent runs.

FIGURE 1 Pseudo code of IWOA
Above detailed explanations, yield the inference that the IWOA technique gives better outcomes in comparison to WOA, PSO, GSA, and DE algorithms for five functions (F1, F2, F3, F4, and F7) out of seven functions. Whereas, for the function F5 this proposed algorithm outperforms only PSO, GSA, and function F6 yields better for IWOA in comparison with original WOA only. From Table 1, it is obtained that the capability of exploitation is high for IWOA technique.

From Table 2, it is quite clear that by adopting IWOA technique one can explore the search space extensively for identifying the favourable spots. It yields better performance in comparison to above-mentioned algorithms for the multimodal functions (F9-F11). For the function F12 and F13, the proposed algorithm gives competitive results. Whereas, for the function F8 this algorithm was unable to impart an improved result. The evasion of local optima by IWOA draws attention for various applications.

5.2 Optimal strategic bidding using IWOA

Improved whale optimization algorithm exhibits to be the most efficient technique for dispatching the power in restructured power market using strategic bidding and maximizing the profit of suppliers and large buyers. Figure 2 represents the implementing flowchart of suggested IWOA.

6 CASE STUDIES

The modelling of bidding strategy has been analysed on IEEE-30 bus [9], IEEE-57 bus [25] and on Indian practical-75 bus system [32] in a deregulated energy market. The 30-bus, 57-bus and 75-bus system consists of 6, 7 and 15 generating utilities, respectively and two large buyers. The forecasted load demands are chosen as 300 and 1500 MW for 30-bus and 57-bus systems, respectively and 1000 MW for 75-bus system.

At first, the bidding strategy is made on the standard test bus system. Second, it is analysed on modified system that considered two renewable sources individually as wind and solar power. Thereafter, it is analysed on modified system considering both sources at a time. The proposed strategy has been simulated on MATLAB R-2018a, 64GB having 4GB RAM, i5 Core Processor environment. The IWOA is tested preferring search agent, maximum number of iteration as 30 and 500, respectively. The number of independent run is chosen as 30.

For the estimation of renewable wind source, an average wind speed for 1 h of July 2008 of Blandford, USA [37] is used considering hub height of 50 m. The air density is 1.242 Kg/m². The power curve of average wind speed for VESTAS V136 having 3.45 MW wind turbine [38] is used in this proposed work for the measurement of wind power. Taking historical data of specified wind speed into account a model is formed for wind speed using different possible PDFs (Weibull, Normal and Rayleigh) as depicted in Figure 3 and among them Weibull PDF is found to be most appropriate as the data are fit to the distribution in the finest way. After taking the mean and deviation of the wind speed, the value of shape and scale parameter as obtained as 2.45 and 4.64, respectively. For accuracy 1000 scenarios are generated for wind speed and converted to power scenarios at required hub height. After scenario generation, scenario reduction is done by using probability distance approach known as Kantorovich distance [34] for making wind power model considering its uncertainty. Here, 1000 scenarios were generated at first and from them 10 reduced scenarios were obtained using probability distance [34]. The corresponding output of reduced scenarios and its occurrence of probability is given in Table 3. From this reduced scenario the feasible power of wind source was obtained to be 52.85 MW using Equation (40).

Similarly, for estimation of solar power, a single hour of solar irradiation historical data [39] is considered for the year of 2013 of Blandford, USA. Solar PV module [40] is used for obtaining the solar power from solar irradiation. The historical data of solar irradiation is applied to different PDFs (Beta, Normal and Rayleigh) for modelling, as depicted in Figure 4 and among them Beta PDF is found to be most appropriate as the data are fit to the distribution in the finest way. After taking the mean and deviation of solar irradiation, the shape parameters α, β used by Equation (32) were obtained as 1.425 and 1.364, respec-
TABLE 3 Wind and solar output power of reduced scenarios and its probability of occurrence

| Reduced scenario index | Reduced scenario index | Wind source | Wind source | Solar source | Solar source |
|------------------------|------------------------|-------------|-------------|-------------|-------------|
|                        |                        | Power output | Probability of occurrence | Power output | Probability of occurrence |
| 1                      |                        | 28.63       | 0.0025      | 27.36       | 0.0265      |
| 2                      |                        | 43.46       | 0.2392      | 39.77       | 0.1850      |
| 3                      |                        | 45.08       | 0.4372      | 52.06       | 0.0316      |
| 4                      |                        | 56.87       | 0.1481      | 71.26       | 0.2954      |
| 5                      |                        | 70.81       | 0.0423      | 83.91       | 0.3252      |
| 6                      |                        | 76.89       | 0.0134      | 96.1        | 0.0182      |
| 7                      |                        | 86.42       | 0.1095      | 104.21      | 0.1060      |
| 8                      |                        | 90.31       | 0.0024      | 117.63      | 0.0087      |
| 9                      |                        | 96.63       | 0.0048      | 138.27      | 0.0026      |
| 10                     |                        | 110.03      | 0.0007      | 150.15      | 0.0009      |

FIGURE 4 Different PDFs of solar irradiation

6.1 | CASE 1: IEEE-30 bus system

6.1.1 | Optimal bidding strategy without renewable sources

The input data used for this case is taken from ref. [9] and elasticity factor \( k \) is chosen as 5. The bidding parameters are mostly needed for making bidding strategy in competitive power market. Therefore, it is determined using joint PDF as given by Equation (22) and optimized using proposed IWOA technique. For profit maximization, these bidding coefficients cannot be chosen individually for generating utilities and buyers. Therefore, here each utility and buyer mentioned one bidding coefficient \((\alpha_{u}, \beta_{u})\) and other coefficients \((\beta_{w}, h)\) are determined by using IWOA considering the range between \([\beta_{w}, 20\beta_{w}]\) and \([h_{u}, 20h_{u}]\). The optimized bidding parameters are given in Table 4. Then it is required to find MCP using optimized bidding parameter. Now using MCP, net profit of generating utilities and large buyers and total power dispatch are calculated for this case. The outcomes thereof have been compared with different optimization techniques like MC [7], GSA [25] and WOA [31] and summarized in Table 4.

From Table 4 it is perceived that total profit of the system is increased to 4994.18 for IWOA in contrast with other techniques. The market is cleared at MCP value 16.645$/MW which is highest when compared with MCP values obtained as 16.35, 16.47 and 16.52$/MW by MC, GSA and WOA respectively. Due to increase of MCP, the power dispatch increases to 533.28 MW. Thus, the proposed IWOA technique outperforms over the aforementioned algorithms.

6.1.2 | Optimal bidding strategy considering a source of wind only, a source of solar only and considering both renewable sources

To measure the impact of renewable sources on model of bidding strategy, in this case wind and solar sources are considered individually along with thermal generating utilities. Due to renewable sources, SO modifies the system’s existing demand by excluding the generation of wind and solar power. The bidding parameters and MCP value are optimized with respect to the modified system demand for wind and solar. Costs of renewable sources are calculated considering uncertainties associated with the sources. For evaluation of overestimation and underestimation cost, the value of coefficient \( \kappa_{oc} \) and \( \kappa_{uc} \) are taken from [25]. For this case, in Table 5 the outcomes were summarised.

Referring to Table 5, it is obtained that MCP values only for wind source is 16.11$/MW and only for solar source is 15.96$/MW. These MCP values are reduced correspondingly from the previous value obtained from Table 4 that is 16.645$/MW using IWOA without renewable sources. Since MCP values were reduced, thermal generations for wind and solar sources were reduced to 490.42 and 479.26 MW, respectively whereas total power dispatch for wind and solar sources were increased to 543.27 and 550.22 MW, respectively in comparison to 533.28 MW obtained by IWOA without any sources. Due to less MCP, demand of large buyers increases for both wind and solar as 323.81 and 332.02 MW, respectively. In addition, the total profit of the system increases to 5092.07 and 5413.94$ as the inclusion of wind and solar, respectively.

The significant generation of power from both the renewable energy sources that is wind and solar energy has an impact on bidding strategy. It clears the market at very low MCP value 15.52$/MW. So, more number of large buyers are interested to buy more power which increases total power dispatch to 551.23 MW from 533.28 MW, obtained without renewable sources. From this table, it is apparent that if both energy sources are taken into account simultaneously, then the necessity of power dispatch from thermal generating sources is decreased to 425.42 MW and power demand by large buyers increases to 329.03 MW. Cost of renewable sources is calculated as 518.82$ for wind and 480.36$ for solar considering the uncertainties. Since the cost of overestimation is less in contrast to cost
## TABLE 4  Optimized bidding coefficients, power dispatch and profit of generating utilities and large buyers without renewable sources

| Generating utilities | MC [7] | GSA [25] | WOA [31] | IWOA |
|----------------------|--------|----------|----------|------|
|                      | $\beta_m$ | $P_t$ | Profit | $\beta_m$ | $P_t$ | Profit | $\beta_m$ | $P_t$ | Profit | $\beta_m$ | $P_t$ | Profit |
| G1                   | 0.0292  | 160    | 1368    | 0.03757 | 160 | 1386.6 | 0.0568 | 160 | 1395.3 | 0.0535  | 160 | 1416.5 |
| G2                   | 0.1242  | 89.37  | 572.69  | 0.11926 | 114.2 | 596.2 | 0.1082 | 106.14 | 604.85 | 0.0881  | 107.23 | 618.21 |
| G3                   | 0.2923  | 45.67  | 322.90  | 0.44963 | 50.09 | 329.52 | 0.5910 | 49.07 | 332.39 | 0.6910  | 47.97 | 338.14 |
| G4                   | 0.0743  | 88.79  | 386.40  | 0.09846 | 88.35 | 395.73 | 0.0596 | 120 | 447.91 | 0.0996  | 119.9 | 462.72 |
| G5                   | 0.1705  | 43.09  | 177.45  | 0.67305 | 40.15 | 178.85 | 0.7158 | 48.87 | 188.39 | 0.708   | 49.06 | 194.54 |
| G6                   | 0.1705  | 43.09  | 177.45  | 0.67305 | 40.15 | 178.85 | 0.7158 | 48.87 | 188.39 | 0.708   | 49.06 | 194.54 |
| Large buyers         | $b_s$  | $D_t$  | Profit | $b_s$  | $D_t$  | Profit | $b_s$  | $D_t$  | Profit | $b_s$  | $D_t$  | Profit |
| B1                   | 0.1705  | 139.70 | 1126.26 | 0.09049 | 149.6 | 1129.4 | 0.1083 | 172.77 | 1134.8 | 0.1155 | 174.25 | 1158.2 |
| B2                   | 0.0771  | 112.06 | 592.6  | 0.06789 | 125.7 | 597.8 | 0.0805 | 142.61 | 599.06 | 0.0788 | 141.62 | 611.66 |
| MCP                  | 16.35   |        |        |        |        |        |        |        |        |        |        |        |
| Total power dispatch by G. U. | 470.1 | 492.2 | 532.69 | 533.28 |
| Total power of L. B. | 251.8 | 275.3 | 315.29 | 315.89 |
| Total Profit         | 4623.75 | 4793.8 | 4890.9 | 4994.1 |

## TABLE 5  Optimized power dispatch and profit of generating utilities and large buyers considering only wind and only solar using IWOA

| Generating utilities (G.U.) | Considering only Wind source | Considering only Solar source | Considering both wind and solar source |
|-----------------------------|-------------------------------|------------------------------|---------------------------------------|
|                             | $\beta_m$ | $P_t$ | Profit | $\beta_m$ | $P_t$ | Profit | $\beta_m$ | $P_t$ | Profit |
| G1                          | 0.0546  | 160 | 1329.5 | 0.0370  | 160 | 1305.5 | 0.0353  | 160 | 1235.2 |
| G2                          | 0.065   | 99.61 | 560.81 | 0.1622  | 93.9 | 542.79 | 0.1014  | 81.61 | 488.49 |
| G3                          | 0.605   | 46.21 | 312.18 | 0.5850  | 43.4 | 303.48 | 0.612   | 32.03 | 259.97 |
| G4                          | 0.106   | 93.62 | 373.47 | 0.0865  | 97.56 | 364.83 | 0.0952  | 75.35 | 291.03 |
| G5                          | 0.552   | 45.47 | 168.21 | 0.545   | 42.15 | 160.1  | 0.641   | 38.2 | 139.63 |
| G6                          | 0.552   | 45.47 | 168.21 | 0.545   | 42.15 | 160.1  | 0.641   | 38.2 | 139.63 |
| Large buyers (L. B.)        | $b_s$  | $D_t$  | Profit | $b_s$  | $D_t$  | Profit | $b_s$  | $D_t$  | Profit |
| B1                          | 0.0873  | 177.52 | 1203.5 | 0.0912  | 182.02 | 1230.4 | 0.0872  | 179.26 | 1310.3 |
| B2                          | 0.0664  | 146.28 | 658.56 | 0.0589  | 150 | 681.05 | 0.0543  | 149.76 | 746.87 |
| MCP                         | 16.11   |        |        |        |        |        |        |        |        |
| Total power dispatch by G.U. | 490.42 | 479.26 | 425.42 | 428.76 |
| Total power demand of L. B. | 323.81 | 332.02 | 329.03 | 328.03 |
| Renewable power dispatch   | 52.85   |        |        |        |        |        |        |        |        |
| Cost of underestimation     | 473.28  |        |        |        |        |        |        |        |        |
| Cost of overestimation      | 62.34   |        |        |        |        |        |        |        |        |
| Total cost of renewable sources | 535.62 | 498.80 | 518.82 | 480.36 |
| Profit of renewable sources | 315.77  | 665.64 | 301.42 | 651.99 |
| Total power dispatch        | 543.27  | 550.22 | 551.23 | 551.23 |
| Total profit                | 5092.07 | 5413.94 | 5554.51 | 5554.51 |
of underestimation, it will encourage utilities providing renewable sources for bidding more power. Total profit for this case is also increased to $5554.51 with respect to the other cases.

From the above comparative analysis of 30-bus system, it is found that the parameters required for bidding, attained by IWOA technique are optimised and also it gives maximum profit as compared to MC [7], GSA [25], and WOA [31] techniques. Figure 5 shows the convergence characteristics of the proposed approach with other approaches. From this characteristic curve, it is seen that the IWOA approach converges faster with respect to others. From table 6 which shows the comparative analysis of 30-bus system, it can be implied that the deviation is minimum for IWOA technique in contrast to others for 30-bus system. So, the accuracy of the proposed technique is higher for providing high profit to the suppliers and buyers. The applied approach that is, IWOA achieves faster convergence with less CPU operating time and obtains a global optima rather than local optima.

It can be inferred from the relative study that the IWOA technique is more efficient, reliable and feasible for modelling the bidding strategy of IEEE-30 bus system. Subsequently, effectiveness of the proposed technique is being tested for IEEE-57 bus system and also for realistic system that is, practical-75 bus system. Here for 57-bus and practical-75 bus system, the bidding strategy model were analysed for double sided bidding strategy using IWOA technique.

6.2 CASE 2: IEEE-57 bus system

The suggested IWOA technique is similarly analysed on IEEE-57 bus test system. The input data used here is taken from [25] and elasticity factor $k$ is chosen as five. The bidding strategy is modelled without renewable sources and with renewable sources considering wind and solar individually and both source at a time. The outcomes obtained thereof are tabulated in Table 7.

6.2.1 Optimal bidding strategy without renewable sources

For this case, determination of MCP is done first using optimized bidding parameter in competitive power market. Then total profit of generating utilities and large buyers, total power dispatch are computed, which are tabulated in Table 7. Analysing this table, it is observed that market is ended at MCP value of $12.57/MW using IWOA without renewable sources. The profit of generating utilities and large buyers are obtained as $15548.7$ and $2796.82$, respectively and total power dispatch is $1730.7$ MW by proposed IWOA method.

6.2.2 Optimal bidding strategy with source of wind only, with source of solar only and considering both the renewable sources

When renewable sources are considered to model the bidding strategy, then SO changes the present demand of the system by subtracting the generation of wind and solar power from actual demand. Bidding coefficients and MCP value are obtained using modified demand. The cost is calculated for renewable sources considering their uncertainty by finding overestimation and underestimation cost. In this case, first sources are considered individually then combination of both is taken. The consequences obtained by proposed IWOA method are shown in Table 7. From this table, it can be implied that when only wind power source is considered along with thermal sources, MCP value reduces to $12.12$ from $12.57/MW obtained by without renewable sources. Thus, power generation and profit of thermal sources reduces to $1687.3$ MW and $14637$. Whereas, demand of large buyers and total power dispatch are increased to $300.76$ and $1740.15$ MW, respectively from $293.59$ and $1730.7$ MW which are obtained by using IWOA without wind sources. Therefore, profit significantly increases for demand side buyers when wind source is integrated to the system.

Similarly, when only solar source is considered with thermal sources the value of MCP and thermal power generation are obtained as $11.62/MW and 1673.6$ MW which are lesser than without solar renewable sources as well as with wind source only. Due to high generation of solar power, the buyer’s demand and total power dispatch are increased to $304.76$ and $1746.56$ MW, respectively. The overestimation costs obtained by IWOA are found to be $48.78$ and $119.84$ which are less than the underestimate cost of $356.54$ and $240.72$ for wind and solar power, respectively.

When combination of both wind and solar sources along with thermal sources are used for modelling bidding strategy, it affects the MCP value greatly. For this case the market is cleared at very
## TABLE 7  
Optimized power dispatch and profit of generating utilities and large buyers without renewable sources and considering source of wind only, source of solar only and both the renewable sources using IWOA

| Generating utilities (GU.) | Without renewable sources | Considering only wind source | Considering only solar source | Considering both wind and solar source |
|---------------------------|---------------------------|------------------------------|------------------------------|--------------------------------------|
|                           | $\beta_m$ | $P_i$ | Profit | $\beta_m$ | $P_i$ | Profit | $\beta_m$ | $P_i$ | Profit | $\beta_m$ | $P_i$ | Profit |
| G1                        | 0.0149   | 575.99 | 5675.8 |   |   |   | 0.0063   | 575.74 | 5127.1 |   |   | 0.0120 | 575.94 | 4853.3 |
| G2                        | 0.142    | 18.28  | 43.278 | 0.1015  | 16.12 | 31.583 |   | 0.0987  | 19.92 | 28.31  |   | 0.0995 | 18.351 | 17.593 |
| G3                        | 0.0455   | 139.99 | 620.57 | 0.0112  | 103.40 | 438.71 |   | 0.0584  | 111.88 | 412.07 |   | 0.0485 | 58.78  | 210.57 |
| G4                        | 0.142    | 18.28  | 43.278 | 0.1015  | 16.12 | 31.583 |   | 0.0987  | 19.92 | 28.31  |   | 0.0995 | 18.351 | 17.593 |
| G5                        | 0.0207   | 549.89 | 5372.4 | 0.0283  | 549.61 | 5122.5 |   | 0.0268  | 549.54 | 4847.6 |   | 0.0245 | 547.57 | 4570.4 |
| G6                        | 0.1152   | 18.28  | 43.278 | 0.1015  | 16.12 | 31.583 |   | 0.0987  | 19.92 | 28.31  |   | 0.0995 | 18.351 | 17.593 |
| G7                        | 0.0273   | 410    | 3750.1 | 0.0285  | 409.9 | 3564.9 |   | 0.0297  | 376.68 | 3118  |   | 0.0268 | 406.58 | 3141.9 |
| Total profit of G. U.     | 15548.7  | 14637  | 13586  | 12827   |   |   |   |   |   |   |   |   |
| Large buyers (L. B.)      | $b_k$    | $D_i$  | Profit | $b_k$    | $D_i$  | Profit | $b_k$    | $D_i$  | Profit | $b_k$    | $D_i$  | Profit |
| B1                        | 0.0625   | 198.07 | 1883.2 | 0.0825  | 199.98 | 1976.1 |   | 0.2138  | 162.53 | 1930.7 |   | 0.1484 | 175.47 | 2077.4 |
| B2                        | 0.1628   | 95.51  | 913.62 | 0.0998  | 100.77 | 993.35 |   | 0.1090  | 142.16 | 1295.8 |   | 0.0863 | 149.99 | 1403.7 |
| Total profit of L. B.     | 2796.82  | 2969.4 | 3226.4 | 3481.1 |   |   |   |   |   |   |   |   |
| MCP                       | 12.57    | 12.12  | 11.62  | 11.14  |   |   |   |   |   |   |   |   |
| Total power dispatch by G. U. | 1730.7  | 1740.15 | 1746.56 | 1769.81 |   |   |   |   |   |   |   |   |
| Total power demand of L. B. | 293.59  | 300.76 | 304.7  | 325.48 |   |   |   |   |   |   |   |   |
| Renewable power dispatch  | 52.85    | 72.96  | 52.85  | 72.96  |   |   |   |   |   |   |   |   |
| Cost of underestimation   | 356.54   | 240.72 | 338.26 | 229.68 |   |   |   |   |   |   |   |   |
| Cost of overestimation    | 48.78    | 119.84 | 45.42  | 112.52 |   |   |   |   |   |   |   |   |
| Total cost of renewable sources | 405.32  | 360.56 | 383.68 | 342.20 |   |   |   |   |   |   |   |   |
| Profit of renewable sources | 235.2   | 487.24 | 205.069 | 470.574 |   |   |   |   |   |   |   |   |
| Total power dispatch      | 1730.7  | 1740.15 | 1746.56 | 1769.81 |   |   |   |   |   |   |   |   |

Low value of MCP $11.14$/MW which is very less in contrast to other prior cases and it increases total power dispatch of the system to $1769.81$ MW.

### 6.3 CASE 3: Practical 75-bus system

An Indian practical 75-bus system consists of 15 generating utilities. Input data for this practical system is taken from ref. [32] and elasticity factor $k$ is chosen as 10. The bidding strategy is modelled for this case considering double sided bidding where the generating utilities and large buyers take part in the energy market for bidding purpose. At first bidding model is solved without renewable sources using IWOA and compared with GA [32]. Then impact of renewable sources is analysed for this case using IWOA. Outcomes of the comparative study are summarized in Table 8. From this table it can be implied that the market is cleared at MCP of $10.522$/MW by IWOA which is higher than $9.79$/MW attained by GA. Due to the high value of MCP, the total profit of generating utilities and large buyers are increased to $9162.6$ and $2784.6$, respectively and also the power dispatch increases to $1104.8$ MW from $1090.8$ MW obtained by GA approach. But, with inclusion of renewable sources that is, wind and solar to the test system, the MCP value is greatly reduced to $8.45$/MW in addition, total profit attained by the generating utilities significantly reduces to $6405.8$ because of lower MCP value and also thermal generation. However it increases profit of large buyers to $3456.2$. So the implication of renewable sources have a great impact on MCP and total dispatch of generation and lower MCP will satisfy all purchase offers which increases the total bidding power. The overestimation cost of renewables sources is less in contrast to underestimation.

### 7 CONCLUSION

This study represents the relevant execution of IWOA for modelling the optimal bidding strategy in a competitive energy market with the consideration of renewable sources and different market constraints. Modification in the abovementioned optimization algorithm is attained by properly adapting its exploitation and exploration stages. The suggested IWOA technique is made to undergo certain tests using some standard benchmark functions in order to compare its performance with other techniques and apparently found to be the most superior one for
TABLE 8  Optimized power dispatch and profit of generating utilities without renewable sources using GA and IWOA and with considering both the renewable sources using IWOA

| Generating utilities (G. U.) | Without renewable sources using GA | Without renewable sources using IWOA | Considering both wind and solar source using IWOA |
|-----------------------------|-----------------------------------|------------------------------------|-----------------------------------------------|
|                             | \(\beta_m\)  \(P_i\)  Profit     | \(\beta_m\)  \(P_i\)  Profit     | \(\beta_m\)  \(P_i\)  Profit               |
| G1                          | 0.0072  300.96  1726.1           | 0.01592  300.04  1940.6           | 0.0131  291.06  1281.6                     |
| G2                          | 0.0095  110.002  908.12          | 0.01738  110.07  988.66           | 0.0143  105.76  732.06                     |
| G3                          | 0.0106  110.032  885.51          | 0.01724  117.86  1033.3           | 0.0154  70.11  474.82                      |
| G4                          | 0.0099  40.0006  324.77         | 0.01731  40.602  354.04           | 0.0161  40.89  277.18                      |
| G5                          | 0.1024  5.0502  41.49           | 0.3294  5.135  45.95            | 0.1180  5.01  34.38                      |
| G6                          | 0.0113  30.00  239.81           | 0.03158  32.958  287.4           | 0.0268  21.36  142.47                    |
| G7                          | 0.0108  1.4755  11.821          | 0.02792  1.0026  8.7678           | 0.0152  1.447  9.66                      |
| G8                          | 0.0125  20.0822  160.89        | 0.01924  20.04  174.91          | 0.0186  20.07  133.48                    |
| G9                          | 0.0098  69.5161  592.78         | 0.01857  60.137  557.5           | 0.0143  60.84  437.93                    |
| G10                         | 0.0114  202.02  1566            | 0.02038  217.42  1838.8            | 0.0188  150.33  977.13                    |
| G11                         | 0.0096  40.0346  324.48        | 0.01964  40.07  353.54          | 0.178  47.17  318.57                    |
| G12                         | 0.0031  80.0108  748          | 0.00725  80.0  806.53            | 0.0054  94.036  752.6                    |
| G13                         | 0.0093  50.9604  462.58       | 0.01378  50.04  490.93           | 0.0108  50.03  387.13                    |
| G14                         | 0.0107  10.354  85.769       | 0.02482  10.08  90.909            | 0.0219  43.25  298.23                    |
| G15                         | 0.0096  20.2706  177.72      | 0.01386  20.076  190.71         | 0.0124  20  148.55                      |
| Total profit of G. U.       | 8255.8  9162.6  6405.8         | 9162.6 | 6405.8                     |
| Large buyers (L. B.)        | \(k_n\)  \(D_i\)  Profit | \(k_n\)  \(D_i\)  Profit | \(k_n\)  \(D_i\)  Profit |
| B1                          | 0.0751  90.073  1495.9         | 0.0925  102.00  1570.6          | 0.0654  110.09  1887.8                   |
| B2                          | 0.0525  98.6  1208.0          | 0.0768  108.02  1213.9         | 0.0448  121.54  1568.4                   |
| Total profit of L. B.       | 2703.9  2784.6  3456.2         | 10522 | 8.45                     |
| MCP                         | 9.79  | 10522 | 8.45                     |
| Power dispatch by G.U.      | 1090.8  1104.8  1021.3         | 1090.8  1104.8  1021.3         |
| Power demand of L. B.       | 188.67  210.02  231.65         | 188.67  210.02  231.65         |

| Wind | Solar |
|------|------|
| Renewable power dispatch | 52.85 | 72.96 |
| Cost of underestimation | 266.72 | 152.56 |
| Cost of overestimation | 35.37 | 92.83 |
| Cost of renewable sources | 302.09 | 245.39 |
| Profit of renewable sources | 144.49 | 371.12 |
| Total power dispatch | 1090.8 | 1104.8 | 1147.68 |

the present scenario of changes in market strategies. Moreover, the uncertainties of the renewable sources are modelled using Beta distribution and Weibull distribution functions for solar and wind, respectively. The bidding strategy is designed with and without wind and solar power. The profit maximization of each utility considering rival’s information is obtained by normal PDF. The impact of renewable sources on bidding strategy reduces the market clearing price as well as the generation of thermal power and increases total bidding power. The optimal bidding strategies are made for IEEE 30-bus and IEEE 57-bus and practical 75-bus system. The proposed IWOA technique yields the best outcomes as far as consistency and feasibility is concerned for maximizing the profit of the generating utilities and buyers when compared with WOA and GSA techniques.

Nomenclature

- \(P_{w,m}\) and \(P_{s,m}\): Wind and solar power generation of \(m^{th}\) supplier
- \(C_{w,m}(P_{w,m})\): Cost function of solar power utilities
- \(C_{s,m}(P_{s,m})\): Cost function of wind power utilities
- \(C_{m}(P_{m})\): Cost function of thermal utilities
- \(C_{n}(D_{n})\): Cost function of larger consumers.
- \(D_{n}^{min}\) and \(D_{n}^{max}\): Lower and upper demand limit of \(n^{th}\) buyer
- \(l_{m}\): Current at maximum power point
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