Optimal Bidding Strategy for Social Welfare Maximization in Wind Farm Integrated Deregulated Power System using Artificial Gorilla Troops Optimizer Algorithm

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ABSTRACT PoolCo electricity trading is one of the most capable bidding practices for executing a centralized energy market model. In the PoolCo market model, each seller and buyers submit their bid price and bid quantity to the independent market operator which they are ready to sell and buy from the market respectively. The market operator regulates the equilibrium market price and volume by considering the acquiesced bid price and bid quantity to settle the market. The optimal bidding strategy of a wind farm combined system is represented here as a centralized power market model to maximize the social welfare of market participants. Initially, the bid price and bid quantity for consumers and suppliers have been calculated using the Monte-Carlo simulation (MCS) approach. Secondly, a wind farm is incorporated into the system with the help of locational marginal price (LMP). To find the eligible buyers and sellers, the market operator determines market clearing price (MCP) and market clearing volume (MCV) based on the submitted bid price and bid quantity of suppliers and buyers. After obtaining MCP and MCV, the market operator reschedules the supplier’s bid quantity with the help of an artificial gorilla troops optimizer (AGTO) algorithm to maximize social welfare by pleasing the system constraints. The AGTO algorithm is used here for the first time to solve the market-clearing power simulation (MCPS) problem with the integration of wind farms under the Poolco power market. To show the feasibility and effectiveness of the optimal bidding strategy with the integration of wind farm, modified IEEE 14-bus and modified IEEE 30-bus test systems are used in this work. Results obtained by using the AGTO algorithm have been compared with those obtained by other optimization algorithms like artificial bee colony (ABC), particle swarm optimizer (PSO), and slime mould optimizer (SMO) algorithms.

INDEX TERMS Wind Farm, Locational Marginal Price, Monte-Carlo Simulation, Artificial Gorilla Troops Optimizer Algorithm, slime mould optimizer algorithms.

I. INTRODUCTION
Restructuring of the electricity market creates rivalry among all the market players, especially among sellers and buyers. In this market environment, each player tries to maximize their profits while maintaining power system securities and other constraints. This leads to the need for an optimal bidding strategy in the electricity market. Uncertainties involved with electricity price, loads, etc. make bidding approaches more complex. An optimum bidding policy is one of the promising approaches to calculating the profit and alleviating risk in different power markets [1]. Since the bidding in the poolco power market model is competitive, a proper MCV and MCP calculation procedure is required for the energy transaction between generating companies (GENCOs) and distribution companies (DISCOs). In this scenario, market-clearing
power simulation (MCPS) should be computationally efficient as MCPS gives the MCV and MCP. Consequently, a variety of research work has already been done by several researchers for designing an efficient MCPS method for electricity trading in the deregulated power market. Game theory and non-cooperative game models are introduced to solve the multi-microgrid real-time electricity market trading mechanism [2]. In competitive electricity market trading, the main objective is to maximize the profits of market participants by minimizing the system risk. To do this, the Lagrangian relaxation (LR) method is used to serve the load obligations in different electricity markets [3]. A new mixed-integer linear programming ( MILP) optimization model can be used in a day-a-head market for efficient pricing of power and reserve services in a large-scale real-time power market [4].

The incorporation of renewable energy sources in generation makes bidding strategies more complex due to uncertainties involved with renewable generation due to its intermittent nature. An optimal bidding strategy is formulated via a bi-level problem for wind power producers in pay-as-bid power markets to maximize their earnings [5]. Considering uncertainty in market price, demand, and renewable generation, a probabilistic optimization method is used to produce optimal bidding curves for an aggregator participating in day-ahead and intra-day markets [6]. An optimal coordinated bidding strategy for power producers of conventional and wind power is presented in the day-ahead electricity market considering uncertainty in wind power and rival’s behavior [7]. A mixed-integer nonlinear programming bidding strategy model is proposed for renewable integrated micro-grid to participate in the day-ahead energy markets considering the uncertainties of load, renewable energy resources, and their outages [8]. A bi-level optimization model-based bidding strategy for risk-based profit maximization and generation cost minimization for wind integrated energy system is presented in ref [9].

Considering uncertainty in day-ahead wind power production, the environmental conditions, and electricity prices, a novel bidding strategy for a wind farm coupled with an energy storage system is formulated in a day-ahead energy market environment [10]. To analyze the effect of penetration of renewable energy resources (REs), a system dynamic approach is used in the gas market and electricity market consisting of wind power generation [11]. To minimize the net cost of energy usage by the buildings considering flexible loads and other energy resources such as PV and battery storage systems, a price responsive operational model is developed with the help of a linearized economic model predictive controller [12]. To enhance the interconnection of microgrid and other renewable energy sources (REs) usages, the distribution system restoration method is implemented using a binary linear programming model considering uncertainty information of RESs power production [13].

Generally, energy storage systems are integrated with renewable energy sources to mitigate imbalances costs that occurred due to forecast errors in the day ahead or short-term electricity markets. To minimize the uncertainty of wind power and improve social welfare, a pumped hydroelectric storage system is integrated into the deregulated power system [14]. An approach to coordinate the decentralized transitive energy for flexible energy resources at the distribution level is proposed to minimize the system risk with proper return. Here, bilateral supply-side bidding is individually determined by using a Markowitz Portfolio Optimization model [15]. Ashery et al. [16] have proposed a stochastic optimization bidding model for a wind power integrated day-ahead market. To minimize the energy storage cost, an optimized energy management strategy (EMS) for PV power plants with an energy storage system (ESS) is described in ref [17].

Considering intermittent output of wind farm, solar PV, and market price, an optimal bidding strategy is formulated as a hybrid stochastic optimization model for a micro-grid containing wind, PV, battery, fuel cell, micro-turbine, diesel generator, and price responsive load [18]. An optimized coordinated bidding strategy for the wind, solar, and pumped storage cooperative (WSPC) model is implemented to facilitate revenue distribution among participating members in the day-ahead large-scale power market [19]. Shen et al. [20] discussed the optimal scheduling and bidding strategy of PV systems with battery energy storage (BES) integrated residential customers in day-ahead (DA) and real-time (RT) markets based on real-time electricity price (RTP) to maximize the profits for load aggregator. A three-stage stochastic optimization problem formulated for the joint operation of a compressed air energy storage (CAES) aggregator and a wind power aggregator which participates in the day ahead, intra-day, and balancing markets considering uncertainty in wind power and electricity price [21].

A genetic algorithm-based optimal bidding of power producer and customer in the day-ahead electricity market is formulated under a pay-as-bid market clearing price (MCP) [22]. Symbiotic organism search (SOS) based dynamic economic dispatch problem is formulated to allocate power to GENCOs and DISCOs for minimizing the generation cost considering other system and network constraints [23]. A multi-objective optimal bidding strategy for GENCOs participating in the electricity market is framed and solved using the modified water wave optimization (MWWO) method [24]. Considering uncertainty in electricity price and wind power, a multi-objective bidding strategy is formulated for a wind-thermal-photovoltaic power system for maximizing profit and minimizing emissions in deregulated power system [25].
In recent years, Artificial Intelligence (AI) based forecasting approaches have gained significant traction for their notable advantage of assuring a certain level of estimation accuracy compared to the statistical model. A hybrid electricity price forecasting technique based on an efficient artificial cooperative search algorithm (ACS) along with an artificial neural network (ANN) method has been used for enhancing the accuracy of the price forecasting compared to existing forecasting methods [26]. Another hybrid approach consisting of a backtracking search algorithm (BSA) and support vector regression (SVR) is used to improve the precision of the forecasting in the Ontario energy market [27].

For analyzing the uncertainty in electricity price and load, the MCS model is very much useful. MCS method is used to capture the random parameters representing uncertainties in energy supply and demands [28]. To analyze the optimal bidding price for investors participating in an energy auction market, the unique Bayesian Nash equilibrium of the game constituted with the integration of the least-squares MCS model has been incorporated [29]. MCS method is used to allocate the electricity capacities, bilateral contract price, and spot market for designing market and electricity trading in the Turkish electricity market [30]. To minimize the energy imbalances, symmetric imbalance charges of peer-to-peer (P2P) market participants are calculated using the MCS approach [31].

From the detailed literature, it is noticeable that most of the researchers are focused on optimal bidding policy in DA and RT markets based on the real-time electricity bid price.

The uniqueness of this work is the bid price calculation for both buyers and sellers using the MCS approach and maximizing social welfare with the help of the AGTO algorithm. To verify the effectiveness of this problem, at first MCPS problem is solved without considering the wind integrated system and finally, the MCPS problem has been solved by considering the wind power integrated system. AGTO algorithm with IEEE 14-bus and IEEE 30-bus test systems are incorporated here to analyze the proposed method. The measured results gained by the AGTO algorithm are compared with the ABC, PSO, and SMO algorithms. A fixed 5 MW wind power is integrated into the modified IEEE 14-bus and 30 MW wind power is integrated into the modified IEEE 30-bus test system for verifying the results.

The main contributions of the paper are given as follows:
1. In this market environment, the optimal placement of wind farms is admitted by the LMP of the system.
2. Monte-Carlo simulation is used to decide the bid price of both sellers and buyers.
3. The AGTO algorithm is used here for the first time to solve the MCPS problem with the integration of wind farms under a centralized power market.
4. A comparison is made for social welfare and seller’s surplus with and without considering wind farms by implementing the other three algorithms i.e. ABC, PSO, and SMO algorithms.

In this type of electrical market, direct negotiation between buyers and sellers is not permitted. The Poolco operator is used to determine the market price for electricity irrespective of the location of the sellers and buyers. The buyer needs to pay an excessive amount compared to the market price due to the presence of transmission and distribution charges. As a result, customers’ price is always more than the market price. A limitation of this work is that the proposed method has not yet been implemented and tested for large-scale power systems consisting of variable speed wind power generation in the real-time market environment.

In this paper, section 1 introduces the overview of the problem. Section 2 discusses the LMP calculation method. A brief description of the Monte-Carlo simulation is given in Section 3. Section 4 depicts the wind farm modeling for load flow analysis. Problem formulation with its constraints is mentioned in detail in section 5. Section 6 shows the implementation of the AGTO algorithm whereas section 7 depicts the outcome of the problem and lastly, section 8 indicates the conclusion drawn from the exponent.

II. LOCATIONAL MARGINAL PRICE CALCULATION

In the electricity market environment, LMP is a commonly used bid in the power market, which is highly accepted by all the market participants. Physically, LMP is the optimal cost of supplying the next MW of load at a specific bus connected to the system. It is observed that LMP is the summation of the costs of marginal energy at the reference bus, marginal losses cost, and congestion costs [32].

\[
LMP_i = LMP_i^{ref} + LMP_i^{loss} + LMP_i^{cong} \tag{1}
\]

The values of the three components are varied based on the selection of the reference bus.

\[
LMP_i^{loss} = (DF_i - 1)LMP_i^{ref} \tag{2}
\]

\[
LMP_i^{cong} = -\sum_{k \in K} GSF_{ik} \beta_k \tag{3}
\]

Where DF_i is the delivery factor of bus-i relative to the reference bus. GSF_{ik} is the generation shift factor for bus-i on line-k. \( \beta_k \) is the constraint cost of k. K is the set of the congested transmission line. The constraints cost is the ratio of reduction in total cost and change in constraint flow. In this work, to reduce the complexity in the calculation, power flow is obtained with the DC model without considering system losses. Here, marginal congestion cost is also neglected. So reference LMP is used as the LMP of the system.

The generation cost of the thermal power plant is given by the following equation [33]:

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\[ C_{\text{gen}}(i) = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \quad \forall i \in N_{\text{gen}} \]  

For a profitable bidding strategy in deregulated electricity market environment, a supplier desires information about the bid prices of other suppliers and consumers. Every supplier is likely to bid its production cost to avoid any loss. Hence their bidding prices can be assumed as normally distributed. Based on their historical data, the normal probability distribution function (pdf) for an \( i \)th supplier can be expressed as:

\[ \text{pdf}(\zeta_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(\zeta_i - \mu_i)^2}{2\sigma_i^2}\right) \]  

Monte-Carlo simulation (MCS) is used to provide a numerical approximate solution to the problem with the inherent probabilistic structure, by performing stochastic simulation and statistical sampling experiments on it [34]. MCS method is used for three types of problems: optimization, numerical, and approximate solution from the probability distribution. MCS techniques are performed based on random numbers and probability statistics include the following steps:

1. Specify the domain and statistical properties of possible inputs.
2. Randomly generate the sets of inputs from a probability distribution function (pdf) in the domain.
3. Perform deterministic calculation with all sets of inputs generated in the previous step.
4. Accumulate the results and analyse them statistically to produce final results (approximate solution).

Random numbers uniformly distributed in \([0,1]\) that are generated using the mixed congruential relationship of the following:

\[ R_{k+1} = ((aR_k + c)|n] \]  

With \( R_{k+1} \) is the new number, \( R_k \) is an old number, \( a \) and \( c \) are non-negative integer coefficients. Where \( e \) and \( n \) are chosen such that generated sequences satisfy the randomness test and period of this sequence, \( p \) should be very large. As numbers generated are smaller than \( \frac{1}{10^5} \) and dividing all numbers by ‘\( n \)’ makes the generated numbers in the range of \([0,1]\). After generating random numbers, sampling of random numbers from the respective distribution function is performed using either the inverse transform method or composition method (if pdf can be expressed as a mixture of pdfs), or the rejection method [35]. Classical MCS and quantum MCS are two different classifications of Monte Carlos, in which samples are drawn from probability distributions and using random walk methods respectively.
the presented approach is to maximize the social welfare without considering system losses and is given by:

$$\max(f_{sw}) = \left[ \sum_{j=1}^{B_M}(B_jP_{ Bj}) - \psi_{mkt} \psi_{mkt}^\text{vol} \right]$$

(11)

Here $B_j$ is the bid price of the buyer, $P_{ Bj}$ is the bid quantity of the buyers, $\psi_{mkt}$ and $\psi_{mkt}^\text{vol}$ are the market-clearing price and market-clearing volume, $S_i$ and $P_{ Si}$ are the seller's bid price and bid quantity, $S_{wp}$ and $P_{ wp}$ are the wind power bid price and amount of wind power willing to sell in the market, $f_{sw}$ is the amount social welfare, $S_N$ and $B_M$ are the numbers of sellers and number of buyers in the market. The equation (7) is solved subject to fulfilling the following constraints:

$$\sum_{j=1}^{B_M} P_{ Bj} + D_{PL} = \sum_{i=1}^{S_N} P_{ Si} + P_{ wp}$$

(12)

Where $D_{PL}$ is the dumped load of the system, Where $P_{ Si}^{\text{min}}, P_{ Si}^{\text{max}}$ is the minimum and maximum real power limit of sellers, $Q_{ Si}^{\text{min}}, Q_{ Si}^{\text{max}}$ is the minimum and maximum reactive power limit of sellers, $V_k$ is the reactive power injected into the power system, $N_L$ is the number of transmission lines, $V_k$ is the voltage magnitude of bus k, $\theta_k$ is voltage angle of bus k. $V_k^{\text{min}}$ is the lower voltage limit of bus k, $V_k^{\text{max}}$ is the upper voltage limit of bus k, $N_b$ is the number of buses, $\psi_{ k}^{\text{min}}$ is the lower phase angle limit of voltage at bus k, $\psi_{ k}^{\text{max}}$ is upper phase angle limit of voltage at bus k, $T_{L}^{\text{flow}}$ is the actual line flow of transmission line L, $T_{L}^{\text{flow max}}$ is the maximum line flow limit of transmission line L, $N_{L}^{T}$ is the number of transmission lines, $T_{\text{tap min}}$ and $T_{\text{tap max}}$ are the minima and maximum limit of transformer tap, $N_{tx}$ is the number of the transformer.

**VI. IMPLEMENTATION OF ARTIFICIAL GORILLA TROOPS OPTIMIZER ALGORITHM**

Inspire by gorilla’s group behavior i.e. gorillas’ group life when finding the food and their group life together, an artificial gorilla’s troop optimizer (AGTO) algorithm is proposed. AGTO algorithm is composed of the following five strategies among which the first three are for the exploration phase and the last two are for the exploitation phase [38]:

1) Migration to unknown areas increases the exploration of AGTO.
2) Moving to other gorillas increases the balance between exploration and exploitation.
3) Migration towards a known place increases the searching capability in different optimization spaces.
4) Follow the silverback (leader for a group that makes decisions and guides others) which maintains the systematic and continued exploration in individual groups to ease exploitation.
5) Competition for adult female explains or mimic the group expansion fight process by puberty/adult gorillas after choosing adult females.

The exploration phase contains the first three strategies, mathematically formulated by the following equation:

$$x_G(t + 1) = \left\{ \begin{array}{ll}
(U_B - L_B)\eta_1 + L_B & \text{rand} < p \\
\{ (r_2-P)x_i(t) + Q & \text{rand} \geq 0.5 \\
\{ \{ (x(t)\text{-}x_{G}(t))(1-P)\text{+}(t(t)-x_{G}(t))\} & \text{rand}<0.5
\end{array} \right. $$

(19)

Where the $x_G(t + 1), x(t), U_B, L_B, p, x_i(t), x(t)$ and $x_{G}(t)$ represents the gorilla candidate position vector in the next to t iteration, current vector of the gorilla position, upper bound of variables, lower bounds of variable, probability of selecting the migration mechanism to an unknown location, a randomly selected gorilla from the group at t iteration, initial vector of gorilla position and randomly selected vector of gorilla candidate position respectively. $r_1, r_2, r_3$ and $\text{rand}$ are the random numbers between 0 to 1, that are updated in each iteration. The intermediate variables $P, Q, R$ and are derived from the following equations (20), (21), and (22).

$$P = \cos(2\pi_1 + 1) \times (1 - \frac{I_{i}}{I_{\text{max}}})$$

(20)

$$Q = PI$$

(21)

$$R = \text{ZX}(t)$$

(22)

$$Z = [-P, P]$$

(23)

Where $I_{i}$ and $I_{\text{max}}$ represents the current iteration and max iteration number, $\pi_1$, 1 and $Z$ represents the random numbers in the range of [0,1], [-1,1] and [-P,P] respectively. At the end of the exploration phase, all $x_G$ solution is compared, and if $x_G(t) < x(t)$ then $x_G(t)$ solution replaces the $x(t)$ and is considered as a silverback. The exploitation phase consists of the following two strategies with their mathematical formulation is shown below/ describe as

1) **Follow the silverback** (when $P \geq S$, where $S$ is the parameter to be set before optimization)

$$x_G(t + 1) = QM(x(t) - x_{sh}) + x(t)$$

(24)
\[
M = \left( \frac{1}{N} \sum_{i=1}^{N} x_{G_i}(t) \right)^{\frac{1}{g}}
\]

\eqref{m}

\[
g = 2^Q
\]

\eqref{g}

Where \( x(t), x_{sb}, x_{G_i}(t) \) and \( N \) represents the gorilla position vector, silverback gorilla position vector (best solution), each gorilla candidate vector position in iteration \( t \), and some gorillas respectively. The intermediate variables \( M, g, \) and \( P \) can be calculated using equations \eqref{m}, \eqref{g}, and \eqref{p}. 

Where \( F, x_{sb}, a, b, \) and \( V_E \) represent the impact force, a random number in the range of \([0,1]\), vector indicates the degree of violence, a specified value before the optimization operation, and violence effect on the solutions’ dimension. \( N_1 \) and \( N_2 \) represents the normal values in the normal distribution. At the end of the exploitation phase, all \( x_G \) the solution is compared, and if \( x_G(t) < x(t) \) then \( x_G(t) \) the solution replaces the \( x(t) \) and considered as silverback i.e. best solution among the whole population \[38\]. The implementation flow chart of the AGTO algorithm is shown in Fig. 1.

\section{RESULTS AND DISCUSSION}

To show the feasibility and effectiveness of the optimal bidding strategy with the integration of wind power, modified IEEE 14-bus \[39\] and modified IEEE 30-bus \[40\] test systems have been considered. The market model has been solved using AGTO Algorithm. The lower limit and upper limit of suppliers’ bid price have been considered as a marginal cost & three times of marginal cost respectively. Based on their probability distribution functions, MCS has been used to predict the bidding behavior of market participants. The bid price and quantity for both consumers and suppliers are predicated on using MCS containing 1000 scenarios for each simulation, based on historical data available for different consumers and suppliers about their bid price and quantities. For each iteration, the bidding strategies of consumers and suppliers market are fixed according to their distribution functions. The wind farm is integrated into the system based on the highest locational marginal price (LMP) values. The bid price of wind power is assumed to be 4 $/MWh. After obtaining bid price and bid quantity from both suppliers and buyers, the market operator does the market-clearing simulation and determined the equilibrium market and market quantity, which is also known as MCP and MCV. The market-clearing price has been simulated with four different wind energy generation.

\begin{table}[h]
\centering
\caption{Parameters of AGTO, ABC, PSO, and SMO algorithm}
\begin{tabular}{|c|c|c|}
\hline
Algorithms Name & Specific parameter for each meta-heuristic algorithm \\
\hline
AGTO & Number of population \\
& Parameter \( p \) \\
& Parameter \( \beta \) \\
& Parameter \( W \) \\
\hline
ABC & Number of onlooker bees \\
& Number of employed bees \\
& Number of scout bees \\
\hline
PSO & Number of particles \\
& Acceleration co-efficient \\
& Inertia weight \\
\hline
SMO & Population size \\
& Exploration capability \\
& Exploitation capability \\
\hline
\end{tabular}
\end{table}

\(2\) i) Competition for adult female \((\text{when } P < S)\)

\[
x_G(i) = x_{sb} - (x_{sb}F - x(t)F)a
\]

\eqref{competition}

\[
F = 2r_5 - 1
\]

\eqref{F}

\[
a = bV_E
\]

\eqref{a}

\[
V_E = \begin{cases}
N_1 & \text{rand} \geq 0.5 \\
N_2 & \text{rand}<0.5
\end{cases}
\]

\eqref{V_E}
After obtaining MCP and MCP, the market operator reschedules the supplier’s bid quantity with the help of AGTO algorithms to maximize social welfare by fulfilling the system equality and inequality constraints. Results obtained using the AGTO algorithm have been compared with those obtained by other well-known optimization algorithms like ABC, PSO, and SMO. Comparisons are made after 50 trials for each implemented algorithm with 200 iterations. The parameters of AGTO, ABC, PSO, and SMO algorithms are shown in Table 1.

A. Modified IEEE 14 bus system

Modified IEEE 14 bus system consists of 5 generators and 11 loads and 20 transmission lines. The total active and reactive power loads are 259 MW and 81.3 MVar respectively [39]. LMP of modified IEEE 14 bus system is calculated for optimal placement of wind farm in the system. Table 2 gives the LMP of the modified IEEE 14 bus system. From Table-2, it is observed that the highest LMP value lies at bus no 14, so the wind farm is integrated at bus no. 14 with a capacity of 5 MW. To sell the power in the market, the supplier’s offers price bid and corresponding bid quantity to the market operator are calculated using the MCS approach as shown in Table 3. Similarly, to buy power from the market, consumers submit their demand price, and the corresponding demand quantity is calculated using the MCS approach as shown in Table 4.

### Table 2

| Bus no | LMP     |
|--------|---------|
| 1      | 3.2848  |
| 2      | 3.4046  |
| 3      | 3.597   |
| 4      | 3.5444  |
| 5      | 3.4993  |

### Table 3

| Suppliers No | Bus No | Bid price ($/MWh) | Bid quantity (MW) | Capacity (MW) |
|--------------|--------|-------------------|-------------------|---------------|
| 1            | 1      | 10.96348288       | 152.2             | 182.4         |
| 2            | 2      | 10.51343466       | 100               | 130           |
| 3            | 3      | 12.21276951       | 55                | 100           |
| 4            | 6      | 13.2838544        | 50                | 100           |
| 5            | 8      | 20.34523          | 55                | 100           |

### Table 4

| Consumers No | Bus No | Bid price ($/MWh) | Bid quantity (MW) |
|--------------|--------|-------------------|-------------------|
| 1            | 2      | 14.1716           | 20.5608           |
| 2            | 3      | 16.6303           | 88.4157           |
| 3            | 4      | 12.8569           | 32.5487           |
| 4            | 5      | 13.1599           | 10.1108           |

In Table 3 and Table 4, the suppliers' bid price and quantity as well as consumers' bid price and quantity are calculated based on the historical data of the test system with the help of the MCS approach. It is worth to mention that the price forecast for the system will change with the change in load demand. Two different case studies have been designed to test the proposed approach.

**Case 1: Without considering wind farm**

While performing the MCPS without considering wind farms, calculated aggregated suppliers and consumer bidding data are sorted in ascending order and descending order curves respectively and the intersection of the two curves gives the MCP and MCV.

Suppliers one is not participating in this bid as it is considered a slack bus supplier. It is used at the final adjustment of power in the market. Fig. 2 denotes the MCPS without considering wind farms. From fig. 2, eligible consumers are identified as power purchasers for the Poolco power markets.

After finding the eligible participants, the system operator is checked the system security and reschedules the supplier’s quantity with the help of the AGTO algorithm to stabilize the system if required. From The fig. 2, it is observed that the MCP value is 13.3487 $/MWh and the MCV value is 201.6625 MW. So, in this Poolco power market, a maximum of 201.6625 MW of power will be sold to eligible consumers. To stabilize the system and maximize social welfare, suppliers' quantities are rescheduled within their capacity limit with the help of AGTO, PSO, ABC, and SMO algorithms.

![Figure 2. MCPS without wind farm for IEEE 14 bus system](image-url)
Table 5 shows the supplier's dispatch quantity in the PoolCo power market by using four different algorithms. From Table 5, it is observed that maximum social welfare was obtained using the AGTO algorithm, and minimum social welfare was obtained using the PSO algorithm. Similarly, the seller's maximum and minimum surplus are obtained using AGTO and PSO algorithms respectively.

**Case 2: With the integration of a 5 MW wind farm**

In this case, MCPS is solved with the integration of wind farm, aggregated suppliers and consumers bidding data are sorted in ascending order and descending order curves respectively and the intersection of two curves gives the MCP and MCV. Here bid price of a wind farm is assumed to be 4 $/MWh. Fig. 3 denotes the MCPS considering the 5 MW capacity of the wind farm.

From the fig. 3, it is observed that the MCP value is 13.2838 $/MWh and the MCV value is 201.6625 MW. By comparing fig. 2 and fig. 3, it is observed that market power increases with the integration of wind farms but the market price is reduced with the integration of wind farms. Since market price is reduced, consumers will be benefited in this case.

To stabilize the system and to maximize the social welfare considering wind farms, suppliers' quantities are rescheduled within their capacity limit with the help of AGTO, PSO, ABC, and SMO algorithms.

Table 6 shows the supplier's dispatch quantity with the integration of a 5 MW wind farm by using four different algorithms. From Table 6, it is observed that maximum social welfare of 976.5290 $/h is obtained using the AGTO algorithm, and minimum social welfare of 974.6880 $/h is obtained using the PSO algorithm. Similarly, the seller's surplus is obtained using AGTO and PSO algorithms respectively.
maximum and minimum seller surplus values of 457,2499 $/h and 455,4089 $/h are obtained using AGTO and PSO algorithms respectively. The comparison of Seller’s Surplus and Social Welfare with and without wind farm for modified IEEE 14 bus system has shown in Fig. 4 and Fig. 5.

**B. Modified IEEE 30 bus system**

Modified IEEE 30 bus system consists of 6 numbers of suppliers including a slack bus generator and 20 consumers. The total active and reactive power loads are 248.3337 MW and 126.2 MVAr respectively [39]. Table 7 gives the LMP of the modified IEEE 14 bus system. From Table 7 it is observed that bus no. 14 is the highest LMP value compared to all other buses of the modified IEEE 30 bus system, so the wind farm is integrated at bus no 14 with a capacity of 30 MW.

| Bus no | LMP VALUE OF MODIFIED IEEE 30 BUS SYSTEM |
|--------|-----------------------------------------|
| 1      | 3.3080                                  |
| 2      | 3.4303                                  |
| 3      | 3.4890                                  |
| 4      | 3.5416                                  |
| 5      | 3.6582                                  |
| 6      | 3.5738                                  |
| 7      | 3.6454                                  |
| 8      | 3.6148                                  |
| 9      | 3.5800                                  |
| 10     | 3.6113                                  |

| Suppliers No | Bid price ($/MWh) | Bid quantity (MW) | Max Capacity(MW) |
|--------------|-------------------|-------------------|------------------|
| 1            | 2.9237            | 80                | 200              |
| 2            | 2.6787            | 80                | 100              |
| 3            | 4.5654            | 40                | 100              |
| 4            | 1.5559            | 30                | 80               |
| 5            | 4.5060            | 50                | 80               |
| 6            | 4.8535            | 55                | 80               |

| Consumers No | Bid price ($/MWh) | Bid quantity (MW) |
|--------------|-------------------|-------------------|
| 1            | 9.9927            | 21.6849           |
| 2            | 3.4955            | 2.0408            |
| 3            | 20.0741           | 66.6297           |
| 4            | 12.0323           | 22.9191           |
| 5            | 14.9060           | 30.1183           |
| 6            | 8.9339            | 5.8505            |
| 7            | 11.9480           | 11.1318           |
| 8            | 3.9967            | 6.1932            |
| 9            | 8.0358            | 8.1664            |
| 10           | 3.5077            | 3.4848            |
| 11           | 8.5116            | 9.0192            |

To participate suppliers in the Poolco power market, they offer price bid and corresponding bid quantity to the market operator which is obtained by the MCS approach as shown in Table 8. Similarly, to participate in the Poolco power market, consumers submit their demand price bid and corresponding demand quantity to the market operator which is calculated using the MCS approach as shown in Table 9.

**TABLE 8**

**OPTIMAL DISPATCH OF SUPPLIERS WITHOUT CONSIDERING WIND POWER**

**TABLE 9**

**OPTIMAL DISPATCH OF SUPPLIERS CONSIDERING 30 MW WIND FARM**

**Case 1: Without considering wind power**

In this MCPS approach, sellers’ bid prices without integration of wind farm are aggregated in ascending order curve and consumers’ bid prices are sorted in descending order curve and the intersection of two curves gives the MCP and MCV. Suppliers one is not participating in this bid as it is considered a slack bus supplier. It is used at the final adjustment of power in the market. Fig. 6 denotes the...
MCPS approach without considering the wind farm for the modified IEEE 30 bus system. From fig. 6, eligible consumers are identified as power purchasers for this system.

![FIGURE 6. MCPS without wind farm for modified IEEE 30 bus system](image)

After finding the eligible power buyers, the system operator is checked the system security and reschedules the supplier’s quantity with the help of the AGTO algorithm to stabilize the system if required. From fig. 6, it is observed that the MCP value is 4.8535 $/MWh and the MCV value is 225.3138 MW.

So, in this power market, a maximum of 225.3138 MW of power will be sold to eligible consumers. To stabilize the system and maximize social welfare, suppliers' quantities are rescheduled within their capacity limit with the help of AGTO, PSO, ABC, and SMO algorithms.

Case 2: With the integration of a 30 MW wind farm

In this case, MCPS is solved with the integration of a 30 MW wind farm based on the LMP of the system. Here bid price of the wind farm is assumed as 4 $/MWh. After integrating wind farms, aggregated suppliers bidding data are sorted in ascending order curves, aggregated consumers' demand data are sorted in descending order curves and the intersection of the two curves gives the MCP and MCV. Fig. 7 denotes the MCPS considering the 30 MW capacity of the wind farm. From fig. 7, it is observed that the MCP value is 4.5654 $/MWh and the MCV value is 225.3138 MW.

![FIGURE 7. MCPS with the integration of wind farm for modified IEEE 30 bus system](image)

Table 10 shows the supplier’s dispatch quantity in the PoolCo power market by using four different algorithms. From Table 10, it is observed that maximum social welfare of 2512.56 $/h is obtained using the AGTO algorithm, and minimum social welfare of 2510.576 $/h is obtained using the PSO algorithm. Whereas 355.4738 $/h is the maximum seller’s surplus and 401.6889 $/h is the minimum seller’s surplus is obtained using AGTO and PSO algorithms respectively.

![FIGURE 8. Comparative convergence characteristics of wind power](image)

![FIGURE 9. Comparison of Seller’s Surplus with and without wind farm for modified IEEE 30 bus system](image)

Table 11 shows the supplier's dispatch quantity in the power market by using four different algorithms for a modified IEEE 30 bus system with the integration of a 30 MW wind farm. From Table 11, it is observed that maximum social welfare of 2529.274 $/h is obtained using the AGTO algorithm, and minimum social welfare of 2525.315 $/h is obtained using the PSO algorithm. Whereas 355.4738 $/h is
the maximum seller’s surplus and 351.5146 $/h is the minimum seller’s surplus is obtained using AGTO and PSO algorithms respectively. By comparing Table 10 and Table 11, it is observed that with the integration of wind farms, social welfare increases from 2512.560 $/h to 2529.274 $/h using the AGTO algorithm.

![Comparison of Seller’s Surplus with and without wind farm](image)

**FIGURE 10.** Comparison of Seller’s Surplus with and without wind farm for modified IEEE 30 bus system

Fig. 8 represents the comparative convergence characteristics for four different optimization algorithms with the integration of a 30 MW wind farm for a modified IEEE 30 bus system. Fig. 8 explores that social welfare of the system is maximized with considering wind farm in the AGTO algorithm compared to that of PSO, ABC, and SMO algorithms. The comparison of Seller’s Surplus and Social Welfare with and without wind farm for modified IEEE 30 bus system has shown in Fig. 9 and Fig. 10.

**VII. CONCLUSION AND FUTURE WORKS**

In this work, the optimal bidding strategy of a wind farm integrated system is presented to maximize the social welfare of the market participants. The optimal location of the wind farm is determined with the help of the locational marginal price (LMP) of the system. The analysis is carried out by using Monte-Carlo simulation (MCS) with the help of the artificial gorilla troops optimizer (AGTO) algorithm and thereby calculating the market equilibrium point i.e. market-clearing volume (MCV) and clearing price (MCP). The bid price and bid quantity for consumers and suppliers are calculated using the Monte-Carlo simulation (MCS) approach. The AGTO algorithm is used here for the first time for solving the market-clearing power simulation (MCPS) problem with the integration of wind farms under the Poolco power market. Results show that social welfare is increased with the integration of wind farms in the system systems compared to the normal system in a Poolco power market. From the results, it is concluded that, under a Poolco power market, wind farm integration is profitable for market buyers as the value of MCP is reduced with the integration of wind farms in the system. To validate this approach, a modified IEEE 14 bus system and modified IEEE 30 bus system is used, and results obtained by the AGTO algorithm are compared with other well-known optimization algorithms like slime mould optimizer (SMO), artificial bee colony (ABC), and particle swarm optimizer (PSO) algorithm. From the results, it is evident that the AGTO algorithm gives better results compared to the other three optimization algorithms implemented here. This work may be extended with a solar park and variable speed wind power generation integrated system.

**REFERENCES**

[1] Ricardo Faia1, Tiago Pinto, Zita Vale and Juan Manuel Corcho, “Portfolio Optimization of Electricity Markets Participation using Forecasting Error in Risk Formulation”, International Journal of Electrical Power & Energy Systems. vol.129, 106739, 2021.

[2] Zifa Liu, Jianyu Gao, Haxiao Yu, Xinyue Wang, “Operation Mechanism and Strategies for Transactive Electricity Market With Multi-Microgrid in Grid-Connected Mode”, IEEE Access, 2020.

[3] Jun Xu, Peter B. Luh, Yaming Ma, Ernan Ni, Krishnan Kasiviswanathan, “Portfolio Optimization in Deregulated Electricity Markets with Risk Management”, IEEE Trans. Power Syst., vol. 21, no. 4, pp. 1653–1662, 2006, doi: 10.1109/TPWRS.2006.879272.

[4] W. Li and L. Tesfatsion, “A Swing-Contract Market Design for Flexible Service Provision in Electric Power Systems,” Econ. Work. Pap., Jul. 2017. [Online]. Available: http://lib.dr.iastate.edu/econ_workingpapers/21.

[5] Karim Afshar, Farshad Shamshini Ghasv and Nooshin Bigdeli, “Optimal Bidding Strategy of Wind Power Producers in Pay-as-Bid Power Markets”, Renewable Energy, vol. 127, pp. 575-586, 2018.

[6] Xiaolin Ayón, María Ángeles Moreno and Julio Usoala, “Aggregators’ Optimal Bidding Strategy in Sequential Day-Ahead and Intraday Electricity Spot Markets”, Energies, vol.10, iss. 4, pp.450-470, 2017.

[7] Satyendra Singh and Manoj Fozdar, “Optimal Bidding Strategy with the Inclusion of Wind Power Supplier in an Emerging Power Market”, IET Generation, Transmission & Distribution, vol. 13, iss. 10, pp. 1914-1922, 2019.

[8] Sabori Das and Moussumi Basu, “Day-Ahead Optimal Bidding Strategy of Microgrid with Demand Response Program Considering Uncertainties and Outages of Renewable Energy Resources”, Energy, vol. 190, 116441, 2020.

[9] Rajesh Panda and Prashant Kumar Tiwari, “Economic Risk-based Bidding Strategy for Profit maximization of Wind Integrated Day-Ahead and Real-Time Double Auctioned Competitive Power markets”, IET Generation, Transmission & Distribution, vol. 13, no. 2, pp. 209-218, 2019.

[10] Mohammad Ali Lasemi and Ahmad Arabkoohsar, “Optimal Operating Strategy of High-Temperature Heat and Power Storage System coupled with a Wind Farm in Energy Market”, Energy, vol. 210, no. 1185451, 2020.

[11] Mohammad Esmaeili, Midezra Shafie-khah, Jo’ao P.S. Catalão, “A system dynamics approach to study the long-term interaction of the natural gas market and electricity market comprising high penetration of renewable energy resources”, Electrical Power and Energy Systems, vol. 139, pp.1-16, 2022.

[12] M. Ostadijafari, A. Dubey, and N. Yu, “Linearized Price-Responsive HVAC Controller for Optimal Scheduling of Smart Building Loads,” IEEE Trans. Smart Grid, pp. 1–14, 2020, doi: 10.1109/TSG.2020.2965559.

[13] J. C. Bedoya, J. Xie, Y. Wang, X. Zhang, and C.-C. Liu, “Resiliency of Distribution Systems Incorporating Asynchronous Information for System Restoration,” IEEE Access, vol. 7, pp. 101471–101482, 2019, doi: 10.1109/ACCESS.2019.2930907.

[14] Subhojit Dawn, Sadhan Gope, Shreya Shree Das and Tahal Selim Ustun, “Social Welfare Maximization of Competitive Congested Power Market Considering Wind Farm and Pumped Hydroelectric Storage System”, Electronics, vol. 10, no. 21, pp.1-18, 2021.
[15] J. C. Bedoya, M. Ostadjifarya, C.-C. Liu, and A. Dubey, “Decentralized Transaction Energy for Flexible Resources in Distribution Systems,” IEEE Trans. Sustain. Energy, pp. 1–1, 2020, doi: 10.1109/TSTE.2020.3029977.

[16] Mohamed Kareem Al Ashery, Dongliang Xiao and Wei Qiao, “Second-Order Stochastic Dominance Constraints for Risk Management of a Wind Power Producer’s Optimal Bidding Strategy”, IEEE Transactions on Sustainable Energy, vol.11, iss.3, pp. 1404 – 1413, 2020.

[17] H. Beltran, E. Perez, N. Aparicio, and P. Rodriguez, “Daily Solar Energy Estimation for Minimizing Energy Storage Requirements in PV Power Plants,” IEEE Trans. Sustain. Energy, vol. 4, no.2, pp. 474–481, 2013, doi:10.1109/TSTE.2012.2206413.

[18] Guangdong Liu, Yan Xu, and Kevin Tomsovic, “Bidding Strategy for Microgrid in Day-Ahead Market Based on Hybrid Stochastic/Robust Optimization”, IEEE Transactions on Smart Grid, vol. 7, is. 1, pp. 227 – 237, 2016.

[19] Yinpeng Yang, Chao Qin, Yuan Zeng, and Chengshan Wang, “Optimal Coordinated Bidding Strategy of Wind and Solar System with Energy Storage in Day-ahead Market”, Journal of Modern Power Systems and Clean Energy, vol. 10, no. 1, pp. 192–203, 2022.

[20] Hongtao Shen, Peng Tao, Ruigi Lyu, Peng Ren, Xinixin Ge, Fei Wang, “Risk-constrained optimal bidding and scheduling for load aggregators jointly considering customer responsiveness and PV output uncertainty”, Energy Reports, vol. 7, pp. 4722–4732, 2021.

[21] Sahand Ghavidel, Mojtaba Jabbari Ghadi, Ali Azizivazhahed, Jamshid Aghaei, Li Li, and Jiangfeng Zhang, “Risk Constrained Bidding Strategy for a Joint Operation of Wind Power and Compressed Air Energy Storage Aggregators”, IEEE Transactions on Sustainable Energy, vol.11, iss. 1, pp. 457 – 466, 2020.

[22] Somendra P.S. Mathur, Anoop Arya and Manisha Dubey, “Optimal Bidding Strategy for Price Takers and Customers in a Competitive Electricity Market”, Cogent Engineering, vol. 4, iss. 1, 1358545, 2017.

[23] Archana Tiwari, Manjaree Pandit and Hari Mohan Dubey, “Profit Maximization through Bid based Dynamic Power Dispatch using Symbiotic Organism Search”, Journal of Information and Computing Science, Vol. 12, No. 1, pp.003–012, 2017.

[24] Ahmad Azadi Hematabadi and Asghar Akbari Foroud, “Optimizing the Multi-Objective Bidding Strategy using min–max Technique and Modified Water Wave Optimization method”, Neural Computing and Applications, vol. 31, pp.5207–5225, 2019.

[25] Hooman Khalooe, Amir Abdollahi, Miadreza Shafie-Khah, Pierluigi Siano, Sayyad Nouravan, Amjad Anvari-Moghaddam, and P.S.CatalaIo, “Co-Optimized Bidding of an integrated Wind-Thermal-Photovoltaic System in Deregulated Electricity Market under Uncertainties”, Journal of Cleaner Production, vol. 242, 118434, 2020.

[26] Alireza Pourdaryaei, Hazlie Moklis, Hazlee Azil Ilius, S. Hr. Aghay Kaboli, Shameen Ahmad, And Swee Peng Ang, “Hybrid ANF and Artificial Cooperative Search Algorithm to Forecast Short-Term Electricity Price in De-Regulated Electricity Market”, IEEE Access, vol. 7, pp. 125369 – 125386, 2019, doi: 10.1109/ACCESS.2019.2938842.

[27] Alireza Pourdaryaei, Mohammad Mohammadi, MunirAzam Muhammad, Junaid Bin Fakhir Islam, Mazaher Karimi, and Amidaddin Shahriari, “An efficient framework for short-term electricity price forecasting in deregulated power market”, IEEE Access, 2021, doi: 10.1109/ACCESS.2021.3129449.

[28] D. An, Qingyu Yang, Wei Yu, Xinyu Yang, Xinwen Fu and Wei Zhao, “Sto2Auc: A Stochastic Optimal Bidding Strategy for Microgrids”, IEEE Internet of Things Journal, vol. 4, no. 6, pp. 2260-2274, 2017.

[29] Lei Zhu, Li Li and Bin Su, “The Price-Bidding Strategy for Investors in a Renewable Auction: An Option Games–based Study”, Energy Economics, vol. 100, no.105331, 2021.

[30] A.Yucekaya, “Electricity trading for coal-fired power plants in Turkish power market considering uncertainty in spot, derivatives and bilateral contract market”, Renewable and Sustainable Energy Reviews, vol. 159, 112189, 2022. https://doi.org/10.1016/j.rser.2022.112189.

[31] Timothy Capper, Jaise Kuriaikose, Maria Sharma, “Impact of Energy Imbalance on Financial Rewards in Peer-to-Peer Electricity Markets”, IEEE Access, 2022, doi: 10.1109/ACCESS.2022.3176614.

[32] F. Li, J. Pan, and H. Chao, “Marginal Loss Calculation in Competitive Spot Market”, 2004 IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies (DRPT2004), pp. 205-209, 2004, DOI: 10.1109/DRPT.2004.1338494.

[33] Subhojit Dawn, Prashant Kumar Tiwari, and Arup Kumar Goswami, “A Joint Scheduling Optimization Strategy for Wind and Pumped Storage Systems Considering Imbalance Cost & Grid Frequency in Real-Time Competitive Power Market”, International Journal of Renewable Energy Research, vol. 6, no. 4, pp. 1248-1259, 2016.

[34] Ronald W. Shortle and Franklin Mendlivil “Explorations in Monte Carlo Methods” Springer Nature, ISBN - 978-0-387-87836-2, 2009, https://doi.org/10.1007/978-0-387-87837-9.

[35] Zio E. (2013), “Monte Carlo Simulation: The Method. In: The Monte Carlo Simulation Method for System Reliability and Risk Analysis”, Springer Series in Reliability Engineering, Springer, London. https://doi.org/10.1007/978-1-4471-4588-2_3.

[36] A. K. Jain, S. C. Srivastava, S. N. Singh and L. Srivastava, “Bacteria Foraging Optimization Based Bidding Strategy under Transmission Congestion”, IEEE Systems Journal, vol.9, iss.1, pp. 141 – 151, 2015.

[37] Andres E. Feijoo and Jose Cidras, “Modeling of Wind Farms in the Load Flow Analysis”, IEEE Transaction on Power System. vol. 15, no. 1, pp 110 – 115, 2000.

[38] Benyamin Abdollahzadeh, F. Soleimianian Gharechopogh and Seyedad Mirjalili, “Artificial gorilla troops optimizer: A new Nature-inspired Metaheuristic Algorithm for Global Optimization Problems”, International Journal of Intelligent Systems, vol. 36, pp. 5887–5958, 2021.

[39] Hossein Mehdiroupouria, Rui Bo, “Optimal Bidding Strategy for Physical Market Participants with Virtual Bidding Capability in Day A-head Electricity Markets”, IEEE Access, vol. 9, pp. 85392 – 85402, 2021.

[40] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, “MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education”, IEEE Trans. Power Syst., vol. 26, no. 1, pp. 12-19, 2011.

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