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RESEARCH ARTICLE

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 buyer 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. To maximize the social welfare of market participants, the optimal bidding strategy of a wind farm integrated system is represented as a centralized power market model. 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). 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 in order to find the eligible buyers and suppliers. 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 farm. To show the feasibility and effectiveness of the proposed bidding strategy, modified IEEE 14-bus and modified IEEE 30-bus test systems are used here along with a wind farm of 5 MW and 30 MW rated capacity, respectively. Results obtained by using the AGTO algorithm have been compared with those obtained by other optimization algorithms like honey badger algorithm (HBA), 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 optimal bidding strategy is one of the promising approaches to calculating the profit and alleviating risk in different power markets [1]. Since the

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bidding in the poolco power market model is competitive, a proper strategy for the calculation of MCV and MCP is required in the energy transaction between generating companies (GENCOs) and distribution companies (DISCOs). In this scenario, market-clearing power simulation (MCPS) should be computationally efficient, as MCP and MCV are derived from it. Consequently, several research studies have been conducted by several researchers in the area of 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 power generation makes bidding strategies more complex due to uncertainties involved with renewable generation due to its intermittent nature. An optimal bidding strategy is formulated to maximize their earnings via a bi-level problem considering wind power producers in pay-as-bid power markets [5]. Considering uncertainty in market prices, 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]. Consideration of uncertainties in load and renewable energy resources, a mixed-integer nonlinear programming model-based optimal bidding strategy is proposed for renewable integrated micro-grids participating in the day-ahead energy markets [8]. To maximize the risk-based profit and to minimize generation costs for a wind integrated energy system, a bi-level optimization model-based bidding strategy is presented in [9].

Considering uncertainty of 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 under a day-ahead energy market environment [10]. To analyze the effect of renewable energy resources (RESs) penetration, a systematic dynamic approach is used for wind power generation taking part in the gas and electricity market [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 (RESs) usage, the distribution system restoration method is implemented using a binary linear programming model considering the uncertainty in RESs power production [13].

Generally, energy storage systems are integrated with renewable energy sources to mitigate the imbalance costs that occurred due to forecast errors in RESs power production for 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 transactive energy for flexible energy resources at the distribution level is proposed to minimize the system risk along with the 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 the intermittent output of a wind farm, solar PV, and market price, an optimal bidding strategy is formulated as a hybrid stochastic optimization model for a microgrid containing wind, PV, battery, fuel cell, micro-turbine, diesel generator, and price-responsive load [18]. An optimal coordinated bidding strategy for the wind, solar, and pumped storage cooperative (WSPC) is implemented to facilitate the revenue distribution among participating members of the large-scale day-ahead power market [19]. Shen *et al.* [20] discussed the optimal scheduling and bidding strategy for residential customers having PV systems integrated with battery energy storage (BES) and taking part in day-ahead (DA) and real-time (RT) markets to maximize the profits for load aggregators. Considering uncertainty in wind power and electricity prices, a three-stage stochastic optimization problem is formulated for the joint operation of a compressed air energy storage (CAES) aggregator and a wind power aggregator participating in the day ahead, intra-day, and balancing markets [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]. A Symbiotic organism search (SOS) based dynamic economic dispatch problem is formulated to allocate power to GENCOs and DISCOs to minimize the generation cost while satisfying 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 has been constituted with the integration of the least-squares-based MCS model [29]. The MCS method is used to allocate the electricity capacities, bilateral contract prices, and spot market in designing the market and electricity trading for the Turkish electricity market [30]. To minimize the energy imbalances, the 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 farm and finally, the MCPS problem has been solved with considering the wind farm. The 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 HBA, 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 farm in a centralized power market.
4. A comparison is made for social welfare and seller's surplus with and without considering wind farm by implementing the other four algorithms i.e. HBA, 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].

$$\mathrm{LMP_i} = \mathrm{LMP_i^{ref}} + \mathrm{LMP_i^{loss}} + \mathrm{LMP_i^{cong}} \tag{1}$$

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

$$\mathrm{LMP_i^{loss}} = (\mathrm{DF_i} - 1)\mathrm{LMP^{ref}} \tag{2}$$

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

where $\mathrm{DF_i}$ is the delivery factor of bus-i relative to the reference bus. $\mathrm{GSF_{ik}}$ is the generation shift factor for bus-i on line-k. β_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 of the calculation, power flow is obtained with the DC model without considering system losses. Here, the marginal congestion cost is also neglected. So the LMP reference is used as the LMP of the system.

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

$$\mathrm{C_{gen}^{bs}}(i) = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \quad \forall i \in \mathrm{N_{gen}} \tag{4}$$

where $\mathrm{C_{gen}^{bs}}(i)$ is the generation cost for i^{th} generator with a capacity P_i and α_i, β_i and γ_i are the actual cost coefficients of thermal generators. The steps of the LMP calculation can be described as follows:

- *Step 1:* Calculate generation cost at the time of t using Eq. (4) for base case ($\mathrm{C_{gen}^{bs}}(t)$) and store the results.
- *Step 2:* Increasing 1 MW load at bus i.
- *Step 3:* Recalculate generation cost using Eq. (4) for the increased load case $\mathrm{C_{gen}^{ic}}(t)$.

- *Step 4:* LMP at bus-i at the time of t can be defined as follows:

$$\mathrm{LMP} = \mathrm{C}_{\mathrm{gen}}^{\mathrm{ic}}(\mathrm{t}) - \mathrm{C}_{\mathrm{gen}}^{\mathrm{bs}}(\mathrm{t}) \tag{5}$$

- Step 5: Store the value of LMP
- Step 6: Repeat steps 2-5 for all the buses.

III. MONTE CARLO SIMULATION METHOD

Monte-Carlo simulation (MCS) is used to provide a numerical approximate solution to the problem with the inherent probabilistic structure [34]. The MCS method is used for three types of problems: optimization, numerical, and approximate solution from the probability distribution. MCS techniques are based on random numbers and probability statistics and 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 (i.e. an approximate solution).

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

$$\mathrm{R}_{\mathrm{k}+1} = (\mathrm{aR}_{\mathrm{k}} + \mathrm{c})\,|\mathrm{n}| \tag{6}$$

where R_{k+1} is the new number, R_k is an old number, a and c are non-negative integer coefficients. Where c 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 'n' 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 the 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.

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

$$\mathrm{pdf}(\varsigma_{\mathrm{i}}) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{i}}}\exp(-\frac{(\varsigma_{\mathrm{i}} - \mu_{\mathrm{i}})^2}{2\sigma_{\mathrm{i}}^2}) \tag{7}$$

where ρ_i, σ_i and μ_i are the bid price, mean value of bid price, and standard deviation of the bid price of i^{th} supplier [36]. After the formulation of their respective PDFs, the sampling and approximate solutions are found by the MCS approach.

IV. WIND FARM MODELING

To calculate the injected wind power from the wind farm, a load flow model of a wind turbine system has been developed considering a fixed speed wind generator (FSWG) system. In the standalone mode of wind generator operation, the capacitor is connected across the stator terminals of the induction machine, whereas in the grid-connected mode of operation, the induction generator delivers active power to the grid and absorbs reactive power from the grid [37]. The mechanical power output of a wind turbine can be written as:

$$\mathrm{P}_{\mathrm{WP}} = \mathrm{C}_{\mathrm{p}}(\frac{1}{2}\mathrm{dAV}_{\mathrm{w}}^3) = \frac{1}{2}\mathrm{d}\pi\mathrm{R}_{\mathrm{w}}^2\mathrm{V}_{\mathrm{w}}^3\mathrm{C}_{\mathrm{p}} \tag{8}$$

where $\mathrm{R_w}$ is the wind turbine blade radius, $\mathrm{V_w}$ is the wind speed, and d is the air density. Cp is the power coefficient; A is the swept area of the turbine. The Boucherot's theorem is applied to write the reactive power expression of the wind farm [37].

$$\begin{aligned}\mathrm{Q} = {} & \mathrm{V}^2\frac{\mathrm{X_c} - \mathrm{X_m}}{\mathrm{X_C X_m}} + \mathrm{X}\frac{\mathrm{V}_2 + 2\mathrm{RP_{WP}}}{2(\mathrm{R}^2 + \mathrm{X}^2)} \\ & - \mathrm{X}\frac{\sqrt{(\mathrm{V}^2 + 2\mathrm{RP_{WP}}) - 4\mathrm{P}_{\mathrm{WP}}^2(\mathrm{R}^2 + \mathrm{X}^2)}}{2(\mathrm{R}^2 + \mathrm{X}^2)}\end{aligned} \tag{9}$$

$$\mathrm{Q} \approx \mathrm{V}^2\frac{\mathrm{X_c} - \mathrm{X_m}}{\mathrm{X_C X_m}} + \frac{\mathrm{X}}{\mathrm{V}^2}\mathrm{P}_{\mathrm{WP}}^2 \tag{10}$$

Here rated voltage is denoted by V, real power denotes with P_{WP}, a sum of the rotor and stator resistance and leakage reactance are represented by R and X respectively, and capacitors bank reactance is X_c.

V. PROBLEM FORMULATION

The optimal scheduling of generators provides an economic operation of generators connected to an electrical system. Now for calculating the profit, the market-clearing price has to be calculated. Mathematically, the objective function of the presented approach is to maximize the social welfare of the system without considering system losses and is given by:

$$\begin{aligned}\max(\mathrm{f}^{\mathrm{sw}}) = {} & \underbrace{[\sum_{\mathrm{j}=1}^{\mathrm{B_M}}(\mathrm{B_j P_{Bj}}) - \xi_{\mathrm{mkt}}^{\mathrm{pri}}\psi_{\mathrm{mkt}}^{\mathrm{vol}}]}_{\text{Buyers surplus}} \\ & + \underbrace{[\xi_{\mathrm{mkt}}^{\mathrm{pri}}\psi_{\mathrm{mkt}}^{\mathrm{vol}} - \sum_{\mathrm{i}=1}^{\mathrm{S_N}}(\mathrm{S_i P_{Si}}) - \mathrm{S_{wp}P_{wp}}]}_{\text{sellers surplus}}\end{aligned} \tag{11}$$

Here B_j is the bid price of the buyer, P_{Bj} is the bid quantity of the buyers, ξ_{mkt}^{pri} *and* ψ_{mkt}^{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, $\mathrm{S_N}$ and $\mathrm{B_M}$ are the numbers of sellers and number of buyers in the market. The equation (7) is solved subject to fulfilling the following constraints:

$$\sum_{j=1}^{B_M} P_{Bj} + D_{PL} = \sum_{i=1}^{S_N} P_{Si} + P_{wp} \tag{12}$$

$$P_{Si}^{min} \leq P_{Si} \pm \Delta P_{Si} \leq P_{Si}^{max} \quad \forall i \in S_N \tag{13}$$

$$Q_{Si}^{min} \leq Q_{Si} \leq Q_{Si}^{max} \quad \forall i \in S_N \tag{14}$$

$$V_k^{min} \leq V_k \leq V_k^{max} \quad k = 1, 2, 3 \ldots\ldots N_b \tag{15}$$

$$\varphi_k^{min} \leq \varphi_k \leq \varphi_k^{max} \quad k = 1, 2, 3 \ldots . N_b \tag{16}$$

$$T_L^{flow_{act}} \leq T_L^{flow_{max}} \quad L = 1, 2, 3 \ldots\ldots N_L^T \tag{17}$$

$$T_{tap}^{min} \leq T_{tap} \leq T_{tap}^{max} \quad tap = 1 \ldots\ldots N_{tx} \tag{18}$$

where D_{PL} is the dumped load of the system, Where P_{Si}^{min}, P_{Si}^{max} is the minimum and maximum real power limit of sellers, Q_{Si}^{min}, Q_{Si}^{max} is the minimum and maximum reactive power limit of sellers, Q_{Si} is the reactive power injected into the power system, N_L^T is the number of transmission lines, V_k is the voltage magnitude of bus k, φ_k is voltage angle of bus k. V_k^{min} is the lower voltage limit of bus k, V_k^{max} is the upper voltage limit of bus k, N_b is the number of buses, φ_k^{min} is the lower phase angle limit of voltage at bus k, φ_k^{max} is upper phase angle limit of voltage at bus k, T_L^{flow} is the actual line flow of transmission line L, T_L^{max} is the maximum line flow limit of transmission line L, N_L^T is the number of transmission lines, T_{tap}^{min} and T_{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 (a 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, which mimic the group expansion and fight process by puberty gorillas.

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

$$x_G(t+1) = \begin{cases} (U_B - L_B)r_1 + L_B & rand < p \\ (r_2\text{-}P)x_r(t) + QR & rand \geq 0.5 \\ x(i) - Q(Q(x(t) - x_{Gr}(t)) & \\ \quad + r_3(x(t) - x_{Gr}(t))) & rand < 0.5 \end{cases} \tag{19}$$

where the $x_G(t+1)$, $x(t)$, U_B, L_B, p, $x_r(t)$, $x(i)$ and $x_{Gr}(t)$ 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 of the vector of gorilla candidate position respectively. r_1, r_2, r_3, and *rand* are the random numbers between 0 to 1 and are updated in each iteration. The intermediate variables P, Q, and R are derived from the following equations (20), (21), and (22).

$$P = \cos(2r_4 + 1) \times (1 - \frac{It_i}{It_{max}}) \tag{20}$$

$$Q = Pl \tag{21}$$

$$R = ZX(t) \tag{22}$$

$$Z = [-P, P] \tag{23}$$

where It_i and It_{max} represents the current iteration and max iteration number. r_4, l 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

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

$$x_G(t+1) = QM(x(t) - x_{sb}) + x(t) \tag{24}$$

$$M = \left(\left| \frac{1}{N} \sum_{i=1}^{N} x_{Gi}(t) \right|^g \right)^{\frac{1}{g}} \tag{25}$$

$$g = 2^Q \tag{26}$$

where x(t), x_{sb}, $x_{Gi}(t)$ 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 (25), (26), and (21).

ii) **Competition for adult female** (when P< S)

$$x_G(i) = x_{sb} - (x_{sb}F - x(t)F)a \tag{27}$$

$$F = 2r_5 - 1 \tag{28}$$

$$a = bV_E \tag{29}$$

$$V_E = \begin{cases} N_1 & rand \geq 0.5 \\ N_2 & rand < 0.5 \end{cases} \tag{30}$$

where F, r_5, *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

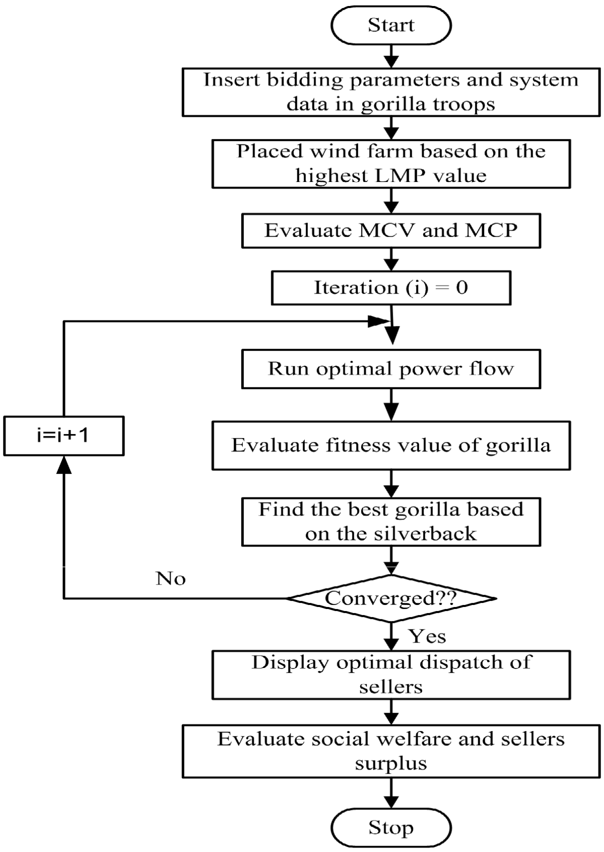

FIGURE 1. Implementation flow chart of artificial gorilla troops Optimizer algorithm.

whole population [38]. The implementation flow chart of the AGTO algorithm is shown in Fig. 1.

VII. 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. Based on historical data available for different consumers and suppliers, the bid price and quantity for both consumers and suppliers are predicated by using MCS containing 1000 scenarios for each simulation. 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 value of the locational marginal price (LMP). 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.

TABLE 1. Parameters of AGTO, HBA, ABC, PSO, and SMO algorithm.

Algorithms Name	Specific parameter for each meta-heuristic algorithm	
AGTO	Number of population	30
	Parameter p	0.03
	Parameter β	3
	Parameter W	0.8
ABC	Number of onlooker bees	30
	Number of employed bees	15
	Number of scout bees	1
PSO	Number of particles	30
	Acceleration co-efficient	0.5
	Inertia weight	1.5
SMO	Population size	30
	Exploration capability	0.05
	Exploitation capability	0.05
HBA [41]	Population size	30
	Constant value (C)	2
	Parameter (β)	6

TABLE 2. LMP of modified IEEE 14 bus system.

Bus no	LMP	Bus no	LMP	Bus No	LMP
1	3.2848	6	3.4975	11	3.5413
2	3.4046	7	3.5489	12	3.5602
3	3.597	8	3.5691	13	3.5695
4	3.5444	9	3.5524	14	3.6330
5	3.4993	10	3.5626		

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's equality and inequality constraints. Results obtained using the AGTO algorithm have been compared with those obtained by other well-known optimization algorithms like HBA, 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.

In Table 3 and Table 4, the suppliers' bid price and quantity as well as consumers' bid price and quantity are calculated

TABLE 3. Suppliers bid price and bid quantity for modified IEEE 14 bus system.

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

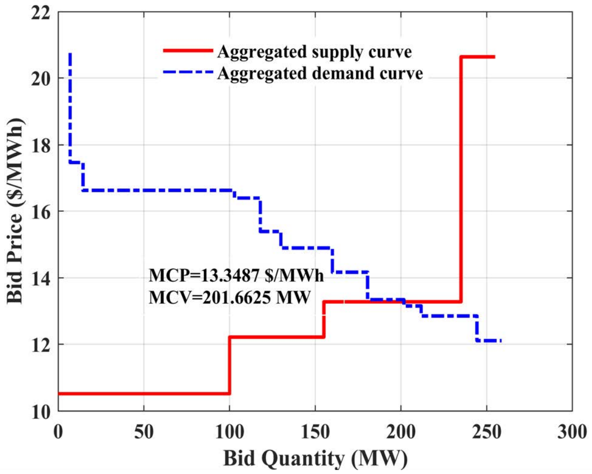

FIGURE 2. MCPS without wind farm for IEEE 14 bus system.

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.

1) 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, HBA, PSO, ABC, and SMO algorithms.

TABLE 4. Consumers bid price and quantity for modified IEEE 14 bus system.

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
5	6	12.1051	14.3131
6	9	14.8907	30.0332
7	10	17.4688	7.4649
8	11	20.7602	6.9917
9	12	15.3861	12.0208
10	13	16.3920	15.0361
11	14	13.3487	21.1393

TABLE 5. Optimal dispatch of suppliers without considering wind power.

Algorithm Name	Supplier-1 (MW)	Supplier-2 (MW)	Supplier-3 (MW)	Supplier-4 (MW)	Supplier-5 (MW)	Sellers Surplus ($/h)	Social Welfare ($/h)
PSO	147.6528	30.8465	16.4574	6.6958	0.00	458.9041	965.1054
ABC	148.0786	30.1659	16.5357	6.7823	0.00	459.2860	965.4873
SMO	148.4532	31.0245	15.352	6.8328	0.00	459.9377	966.1389
AGTO	148.5432	31.3523	15.5425	6.2245	0.00	461.2587	967.4600
HBA	148.3432	31.5523	15.4425	6.3245	0.00	461.2416055	967.4429034

Table 5 shows the supplier's dispatch quantity in the PoolCo power market by using five 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 is obtained using AGTO and PSO algorithms respectively.

2) 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 the market price is reduced, consumers will be benefited in this case. To stabilize the system and to maximize the social welfare considering wind farm, suppliers' quantities are rescheduled within their capacity limit with the help of AGTO, HBA PSO, ABC, and SMO algorithms.

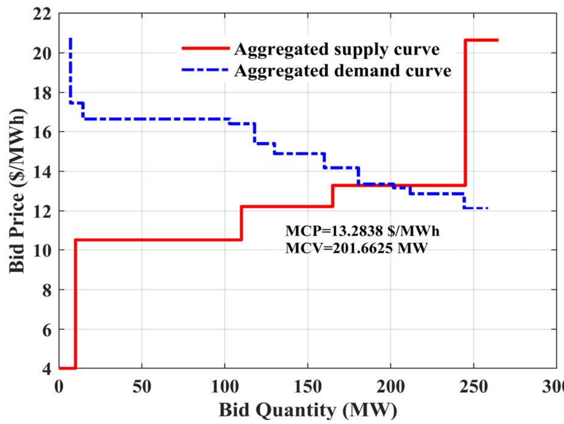

FIGURE 3. MCPS with the integration of 5 MW wind farm for modified IEEE 14 bus system.

TABLE 6. Optimal dispatch of suppliers considering wind power (5 MW).

Algorithm Name	Supplier-1 (MW)	Supplier-2 (MW)	Supplier-3 (MW)	Supplier-4 (MW)	Supplier-5 (MW)	Sellers Surplus ($/h)	Social Welfare ($/h)
PSO	136.5516	22.5629	26.4246	11.0234	0.00	455.4089	974.6880
ABC	136.8227	23.1235	26.2048	10.5115	0.00	456.0272	975.3064
SMO	136.7295	23.4228	26.4077	10.1025	0.00	456.8575	976.1366
AGTO	136.4911	23.7664	26.4018	10.0032	0.00	457.2499	976.5290
HBA	136.4811	23.7764	26.3018	10.1032	0.00	457.1473106	976.4264217

Table 6 shows the supplier's dispatch quantity with the integration of a 5 MW wind farm by using five 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 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.

To participate in the Poolco power market, suppliers 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.

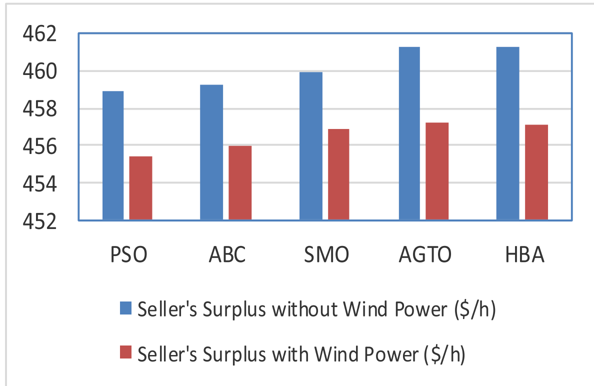

FIGURE 4. Comparison of seller's surplus with and without wind farm for modified IEEE 14 bus system.

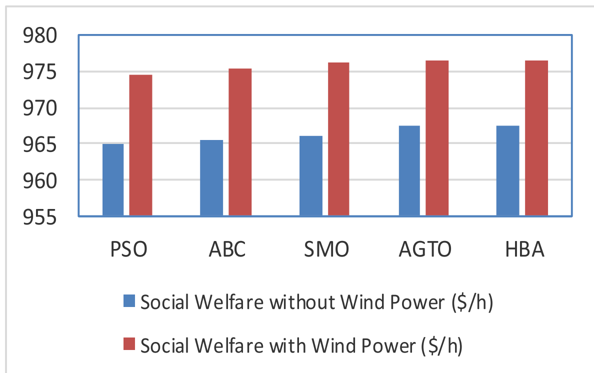

FIGURE 5. Comparison of social welfare with and without wind farm for modified IEEE 14 bus system.

TABLE 7. LMP value of modified IEEE 30 bus system.

Bus no	LMP	Bus no	LMP	Bus No	LMP
1	3.3080	11	3.5752	21	3.6149
2	3.4303	12	3.6827	22	3.6248
3	3.4980	13	3.5471	23	3.6382
4	3.5416	14	4.0695	24	3.6851
5	3.6582	15	3.6468	25	4.0189
6	3.5738	16	3.8368	26	3.7125
7	3.6454	17	3.6020	27	3.6001
8	3.6148	18	3.6428	28	3.5932
9	3.5800	19	3.7019	29	3.6941
10	3.6113	20	3.8075	30	3.7519

TABLE 8. Suppliers bidding data for modified IEEE 30 bus system.

Suppliers No	Bus No	Bid price ($/MWh)	Bid quantity (MW)	Max Capacity(MW)
1	1	2.9237	80	200
2	2	2.6787	80	100
3	13	4.5654	40	100
4	23	1.5559	30	80
5	22	4.5060	50	80
6	27	4.8535	55	80

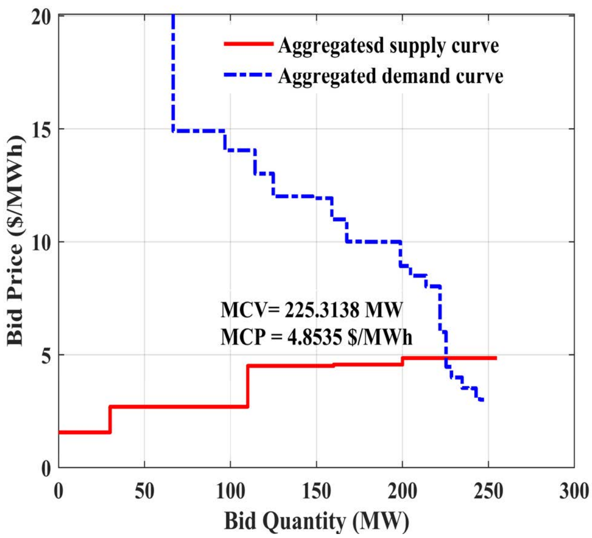

FIGURE 6. MCPS without wind farm for modified IEEE 30 bus system.

1) 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 buyers are identified as power purchasers for this system.

After finding the eligible power buyers, the system operator checks for the system's security and, if required reschedules the supplier's quantity with the help of the AGTO algorithm in order to stabilize the system. From fig. 6, it is observed that the MCP and MCV values are 4.8535 $/MWh and 225.3138 MW respectively.

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

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. 403.6727 $/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.

2) 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

TABLE 9. Consumers bidding data for modified IEEE 30 bus system.

Consumers No	Bus No	Bid price ($/MWh)	Bid quantity (MW)
1	2	9.9927	21.6849
2	3	3.4955	2.4048
3	4	20.0741	66.6297
4	7	12.0323	22.9191
5	8	14.9060	30.1183
6	10	8.9339	5.8505
7	12	11.9480	11.1318
8	14	3.9967	6.1932
9	15	8.0338	8.1664
10	16	3.5077	3.4848
11	17	8.5116	9.0192
12	18	2.9920	3.1777
13	19	10.0072	9.5195
14	20	3.4981	2.2037
15	21	14.0514	17.5111
16	23	4.4671	3.1879
17	24	11.0107	8.6916
18	26	5.9929	3.4724
19	29	3.0158	2.3677
20	30	13.0232	10.5994

TABLE 10. Optimal dispatch of suppliers without considering wind power.

Algorithm Name	Supplier-1 (MW)	Supplier-2 (MW)	Supplier-3 (MW)	Supplier-4 (MW)	Supplier-5 (MW)	Supplier-6 (MW)	Sellers Surplus ($/h)	Social Welfare ($/h)
ABC	49.8678	64.9682	24.1596	45.5292	20.3301	20.4591	401.6889	2510.576
PSO	50.1793	64.2528	24.1111	46.1709	20.1345	20.4652	402.7693	2511.657
SMO	50.3538	65.1841	24.1577	45.5025	19.7287	20.3872	402.7988	2511.686
AGTO	50.6556	63.0647	23.9587	47.0065	19.7217	20.9066	403.6727	2512.560
HBA	50.5538	65.1641	24.0477	45.3225	19.7287	20.4072	402.9527938	2511.840132

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.

Table 11 shows the supplier's dispatch quantity in the power market by using five different algorithms for a modified IEEE 30 bus system with 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

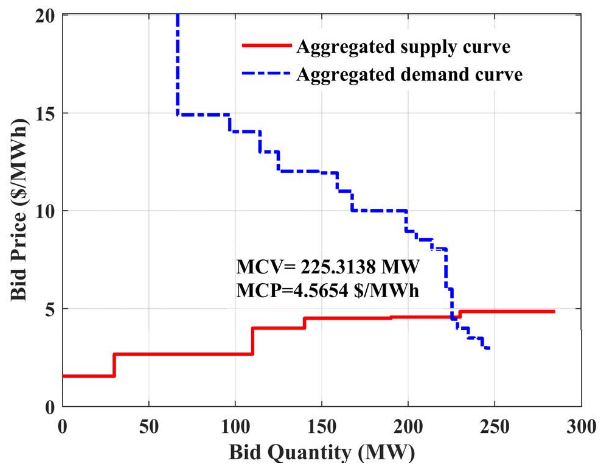

FIGURE 7. MCPS with the integration of wind farm for modified IEEE 30 bus system.

TABLE 11. Optimal dispatch of suppliers considering 30 MW wind farm.

Algorithm Name	Supplier-1 (MW)	Supplier-2 (MW)	Supplier-3 (MW)	Supplier-4 (MW)	Supplier-5 (MW)	Supplier-6 (MW)	Sellers Surplus ($/h)	Social Welfare ($/h)
PSO	48.1023	61.3320	22.93101	46.1438	16.8046	0.0	351.5146	2525.315
ABC	48.3357	62.4345	21.5483	45.7365	17.2588	0.0	352.7791	2526.579
SMO	48.4383	62.1321	21.218	46.1642	17.3612	0.0	353.6702	2527.47
AGTO	47.6258	62.8124	22.7137	46.8201	15.3418	0.0	355.4738	2529.274
HBA	47.5248	62.7324	22.6137	46.8011	15.6418	0.0	355.1177	2528.918

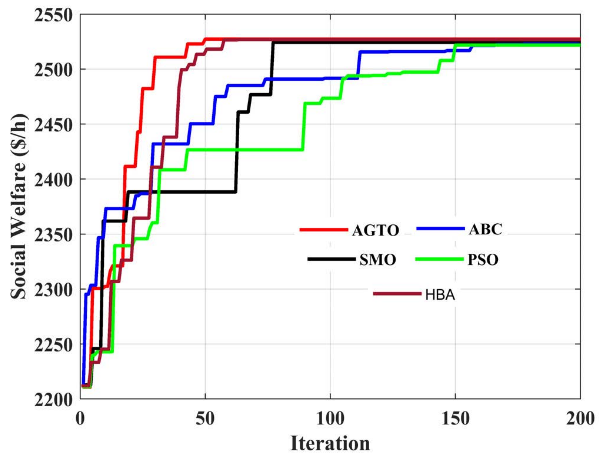

FIGURE 8. Comparative convergence characteristics of wind power.

observed that the social welfare obtained using the AGTO algorithm.

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.

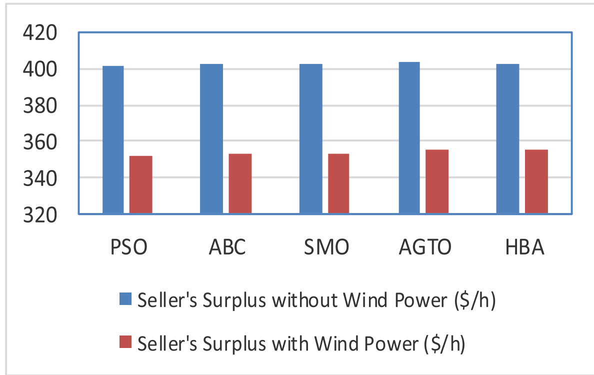

FIGURE 9. Comparison of seller's surplus with and without wind farm for modified IEEE 30 bus system.

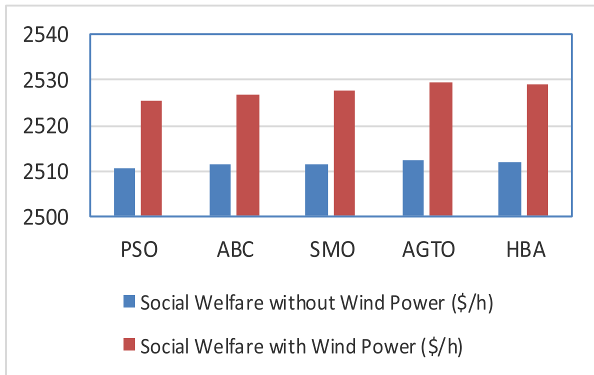

FIGURE 10. Comparison of seller's surplus with and without wind farm for modified IEEE 30 bus system.

VIII. 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 are used, and results obtained by using AGTO algorithm are compared with the other well-known optimization algorithms like honey badger algorithm (HBA), 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 the integration of a solar park and variable speed wind power generation integrated system.

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