Optimal Power Flow of a Power System Incorporating Stochastic Wind Power Based on Modified Moth Swarm Algorithm

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ABSTRACT The combined heat and power (CHP) generator not only generates electrical power but also generates heat energy in a single process, which decreases the emission level significantly. The integration of wind power into the power system will lead to an impact on the economic operation of the system as well as the bus voltage and transmission losses. In this paper, a formulation of optimal power flow (OPF) problem of a power system incorporating stochastic wind power is presented. To solve this problem, a modified version of the moth swarm algorithm (MMSA) is proposed. Three objective functions, which are the minimization of operating cost, the minimization of transmission power loss, and the voltage profile improvement, are considered in this paper. To minimize the operating cost, the direct, overestimation, and underestimation costs of wind power units are considered. Two test systems are considered to prove the effectiveness and the superiority of the proposed MMSA in comparison with other methods. The comparison with other methods proves the efficiency and the superiority of the proposed MMSA.

INDEX TERMS Combined heat and power system, modified moth swarm algorithm, optimal power flow, stochastic wind power, valve point effect.

NOMENCLATURE

\( F \) total optimization function
\( VD \) voltage deviation
\( PL \) power losses
\( F_p, F_h, F_c \) fuel cost of power, heat and cogeneration units
\( C_{ps, d} \) direct cost of the \( d^{th} \) wind power plant
\( C_{pw, d} \) penalty cost of the \( d^{th} \) wind power plant
\( C_{rw, d} \) reserve cost of the \( d^{th} \) wind power plant
\( P_{pi} \) output power of power only unit \( i \)
\( P_{g}, Q_{g} \) active and reactive power for any generator
\( P_{g1} \) active power of the slack bus
\( P_{gmin} \) minimum capacity limit of unit \( i \)
\( P_{cw, d} \) scheduled power of the \( d^{th} \) wind power plant
\( P_{ws, d} \) available power from the \( d^{th} \) wind power plant
\( P_{wr, d} \) rated power of the \( d^{th} \) wind power plant
\( P_{D}, Q_{D} \) system load active and reactive demand
\( H_{bj} \) output heat of heat only unit \( j \)

\( H_{D} \) system heat demand
\( H_{bj}^{\text{min}} \) minimum output heat of heat only unit \( j \)
\( H_{bj}^{\text{max}} \) maximum output heat of heat only unit \( j \)
\( V_{g}, V_{L} \) voltage magnitude at the generator and load buses
\( V_{i}, V_{j} \) voltage magnitude of terminal buses of branch \( z \)
\( V_{u} \) voltage magnitude of the PV and slack buses
\( TS \) transformers tap setting
\( Q_{C} \) VAR compensation
\( S_{l} \) transmission line loading
\( G_{z} \) conductance of the \( z^{th} \) branch
\( \delta_{i}, \delta_{j} \) voltage phase angle of terminal buses of branch \( z \)
\( G_{jl}, B_{jl} \) conductance and susceptance between bus \( j \) and \( l \)
\( \theta_{jl} \) voltage angle difference between bus \( j \) and \( l \)
\( f_{w}(P_{w, d}) \) wind power probability density function
\( S, k, c \) wind speed, shape factor, and scale factor
\( S_{in}, S_{out} \) cut-in and cut-out speeds of wind turbine
\( S_{r} \) rated wind speed of the wind turbine
\( x^{\text{max}}, x^{\text{min}} \) upper and lower limits of variable \( x \)
the value of variable $x$ at current iteration $i$ and next iteration $i + 1$

$x^i_p$

the pathfinder position at current iteration $i$

$\text{best}_g$

global best solution

$\text{best}_p$

pathfinder solution randomly chosen on the basis of its probability value

$\sigma^i$  

normalized dispersal degree at iteration $i$

$\alpha_i, \beta_i, \gamma_i$

fuel cost coefficients of power only unit $i$

$e_i, h_i$

valve point coefficients of unit $i$

$\delta_j, \theta_j, \psi_j$

cost coefficients for heat only unit $j$

$\lambda_k, \mu_k$

cost coefficients for cogeneration unit $k$

$\epsilon_k, \zeta_k, \eta_k, \upsilon_k$

direct and penalty cost coefficients of the $d^{th}$ plant

$g_{r,d}$

reserve cost coefficient for the $d^{th}$ wind plant

$w_1, w_2$

weighting factors defined by the user

$\tau_p, \tau_v, \tau_q$

penalty factors of $P_{g1}, V_L, Q_g, S_i, H_c$ and $H_h$

$\tau_s, \tau_{hc}, \tau_{hh}$

variation coefficient and uniform Gaussian distribution

$\kappa_1, \kappa_2, \kappa_3, r_1, r_2$

random samples from Gaussian distribution

$r_p, r_h$

random numbers between 0 and 1

$n_p, n_h$

number of power only and heat only units

$n_c, n_w$

number of cogeneration and wind power units

$n_T$

number of tap transformers

$n_C$

number of VAR compensators

$n_b, n_L$

number of buses and load buses

$n_t$

number of transmission lines

$N_p, n_p$

number of PV buses plus slack bus

$z$

number of population

$z_f, z_{pr}$

number of pathfinders and prospectors

$\mu^i$

number of current iteration

$max_i$

maximum number of iterations

$z_g, z_a$

number of onlookers that uses the Gaussian stochastic distribution and associative learning mechanism with an immediate memory

I. INTRODUCTION

The key objective of optimal power flow (OPF) is to attain an objective function by adjusting the settings of control variables to meet different constraints [1]. In general, the OPF problem is a complicated problem. Considering the valve point effects, OPF problem shows non-smooth and non-convex characteristics which makes it more complicated [2].

In literature, a significant amount of work has been done to solve the OPF problem with thermal units like particle swarm optimization (PSO) [3], bacterial foraging method (BFA) [4], biogeography-based optimization (BBO) [5], teaching-learning-based optimization (TLBO) [6] and moth swarm algorithm (MSA) [7].

Wind turbines are widely connected to power systems. So, it becomes more important to study the influence of wind turbines on the operation of power systems. The integration of wind turbines to the power systems will affect not only the economic operation of the power system but also the voltage of the buses and transmission power losses [8], [9].

The major challenge in integrating wind power in a power system is its intermittent nature. The power generated from wind power turbines is uncertain and it may be more than the scheduled power leading to underestimation of the available amount. So, the utility operator will pay a penalty cost as extra power goes wasted if not utilized. On the contrary, the generated wind power may be less than the scheduled power leading to overestimation. Therefore, the utility operator needs to have a spinning reserve which increases the total operating cost of the power system [9], [10].

Various optimization methods have been proposed to solve the OPF problem with the inclusion of wind farms. The authors in [11] proposed the modified cuckoo search (CS) method to solve the OPF problem in the presence of wind power. Where the wind associated costs are included in the objective function. In addition, the Q-V formulation of the asynchronous generator is incorporated with the traditional load flow solution. The evolutionary particle swarm optimization (EPSO) method is proposed in [12] to investigate the effect of a wind power generation system on not only power system economic operation but also the voltages of buses and transmission power loss. A novel approach is proposed in [13] for the solution of OPF problem taking into account the uncertainties caused by not only wind generation but also the various factors in the power system where the enhanced PSO with the evidence theory framework is proposed to solve this problem. Also, a robust model against any realization of uncertain parameters is presented in [14] to AC optimal power flow incorporating wind power where both uncertain wind power and system demand are categorized in terms of bounded intervals forming a polyhedral uncertainty set. The probabilistic OPF is solved in [15] using the quasi-Monte Carlo simulation (QMCS) considering the correlation of wind speeds using copula functions.

The combined heat and power (CHP) generators which called cogeneration units provide the users by both power and heat at a single process. In the cogeneration units, the heat produced depends on the generated power and vice versa. The cogeneration units are efficient and environmentally friendly in comparison with the traditional power generation systems which produce power and heat separately [2]. So, the cogeneration units have been widely used in power systems recently. The mutual dependencies of heat and power generation in the cogeneration units leads to a complication in the integration of these units into the OPF problem [16], [17]. A maiden formulation for solution of the dynamic OPF (DOPF) problem considering the cogeneration units is presented in [2]. Where two test systems are employed with different types of thermal generating units, heat only units and cogeneration units. In addition, the bio-inspired Krill Herd (KH) algorithm is proposed to solve this highly complex and non-convex problem.
Moth swarm algorithm (MSA) is one of the newest optimization techniques proposed in [7] based on the behavior of a group of moths while searching food in the dark. The exploration and exploitation abilities of the MSA are improved by employing a Lévy-mutation and learning mechanism with immediate memory.

The MSA is employed to solve successfully the OPF problem, combined economic and emission dispatch problem, and environmental dispatch with valve-point effect problem [7], [18]. The simulation results prove the ability of the MSA to find a better solution than other methods used in the comparison. Nevertheless, the MSA has a drawback which is slow convergence. To treat this drawback, chaotic MSA is proposed in [19] by integrating the original MSA with chaotic maps which help in finding the best numbers of prospectors for increase the exploitation. In addition, a modified version of the MSA is proposed in [20] to solve the OPF problem by employing an arithmetic crossover to improve the convergence speed of the original MSA.

As known, heuristic optimization algorithms do not always guarantee to get the global optimal solution of the problem, but they find a reasonable solution which is near to a globally optimal solution. In addition, the “No Free Lunch” theorem states that there is no single optimization algorithm that can be considered as the best one in solving all optimization problems [21]. Therefore, the researchers are still interested to suggest new optimization algorithms or improve the already existent methods to get a better solution of OPF because the OPF is a key problem in power system operation enhancement.

Therefore, in this paper, a modified moth swarm algorithm (MMSA) is proposed with the purpose of improving the convergence speed, efficiency and the performance of the conventional MSA. The MMSA can be derived by modifying the associative learning mechanism with immediate memory. In addition, the strategy of reducing the number of prospectors is modified in the proposed MMSA. The proposed MMSA is then employed to solve the OPF problem of combined heat and power system incorporating stochastic wind power. The proposed MMSA is evaluated using a modified IEEE 30-bus system and a modified IEEE 118-bus system and compared with some published methods employing the same data. The contributions of this paper are:

- Improving the solution of this problem in comparison with other recently published methods using two test system. In addition, the IEEE 118-bus system is large enough to prove the scalability and validity of the proposed MMSA to solve the real applications of OPF.

The paper is organized as follows: Section II describes the problem formulation. Stochastic wind power model is described in Section III. Section IV introduces the proposed MMSA. Experimental results and comparisons are presented in Section V. Finally, Section VI concludes the work.

II. PROBLEM FORMULATION

Different objective functions which are the minimization of operating cost, minimization of transmission power loss and voltage profile improvement are considered in this work.

A. FUEL COST FUNCTION

1) POWER ONLY UNITS

The fuel cost of power only units can be described as [22], [23]:

\[
F_p = \sum_{i=1}^{n_p} (\alpha_i + \beta_i P_{pi} + \gamma_i P_{pi}^2)
\]

By considering valve point effect, the cost function \(F_p\) can be rewritten as follows [24]:

\[
F_p = \sum_{i=1}^{n_p} (\alpha_i + \beta_i P_{pi} + \gamma_i P_{pi}^2) + |e_i \times \sin(h_i(P_{pi}^{min} - P_{pi}))|
\]

2) HEAT ONLY UNITS

The fuel cost for heat only units can be described as [2]:

\[
F_h = \sum_{j=1}^{n_h} a_j + b_j H_{bj} + c_j H_{bj}^2
\]

3) COGENERATION UNITS

The fuel cost function for cogeneration units can be described as [2]:

\[
F_c = \sum_{k=1}^{n_c} k_h + \mu_k P_{ck} + \nu_k P_{ck}^2 + \epsilon_k P_{ck} H_{ck} + \zeta_k H_{ck} + \eta_k H_{ck}^2
\]

B. COST FUNCTION FOR WIND POWER

As known, wind power turbines require no fuel cost. So, if these turbines are owned by the utility operator, the cost function of wind power can be ignored. Usually, wind power turbines are owned by private parties and the utility operator pay for wind power purchased from these parties [9], [25]. In this case, the wind power cost can be categorized into three parts as follows:
1) DIRECT COST FOR WIND POWER
A direct cost function for wind power derived from the private party can be expressed as follows [9]:

\[ C_{w,d}(P_{ws,d}) = g_d P_{ws,d} \]  

(5)

2) COST DUE TO UNDERESTIMATION OF WIND POWER (PENALTY COST)
The underestimation of wind power occurs when the delivered wind power is higher than the estimated value. So, the utility operator needs to pay for not using available wind power. This cost called penalty cost which can be expressed as follows [9]:

\[ C_{pw,d}(P_{wav,d} - P_{ws,d}) = g_{p,d} \int_{P_{ws,d}}^{P_{wav,d}} (P_{w,d} - P_{ws,d}) f_w(P_{w,d}) dP_{w,d} \]  

(6)

3) COST DUE TO OVERESTIMATION OF WIND POWER (RESERVE COST)
The overestimation of wind power occurs when the delivered wind power is less than the estimated value. So, the utility operator needs to have a spinning reserve. The cost of this spinning reserve can be expressed as follows [9]:

\[ C_{rw,d}(P_{ws,d} - P_{wav,d}) = g_{r,d} \int_{P_{ws,d}}^{P_{wav,d}} (P_{w,d} - P_{ws,d}) f_w(P_{w,d}) dP_{w,d} \]  

(7)

C. POWER LOSS FUNCTION
The transmission power losses in the system can be defined as follows [23]:

\[ P_L = \sum_{z=1}^{n_t} G_z[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j)] \]  

(8)

D. VOLTAGE DEVIATION FUNCTION (VOLTAGE PROFILE IMPROVEMENT)
To get an attractive voltage profile, the load bus voltage deviations from 1.0 per unit is chosen as an objective function as follows [23]:

\[ VD = \sum_{m=1}^{n_L} |V_m - 1| \]  

(9)

E. CONSTRAINTS
1) SYSTEM POWER AND HEAT BALANCE

\[ \sum_{i=1}^{n_p} P_{pi} + \sum_{k=1}^{n_c} P_{ck} + \sum_{d=1}^{n_w} P_{w,d} = P_D + P_L \]  

(10)

\[ \sum_{k=1}^{n_c} H_{ck} + \sum_{j=1}^{n_h} H_{hj} = H_D \]  

(11)

2) LOAD FLOW EQUATIONS:

\[ P_{gj} - P_{Dj} = V_j \sum_{l=1}^{n_b} V_l (G_{jl} \cos \theta_{jl} + B_{jl} \sin \theta_{jl}) \]  

(12)

\[ Q_{gj} - Q_{Dj} = V_j \sum_{l=1}^{n_b} V_l (G_{jl} \sin \theta_{jl} - B_{jl} \cos \theta_{jl}) \]  

(13)

3) GENERATOR CONSTRAINTS

\[ V_{u,min} \leq V_u \leq V_{u,max} \quad u = 1, \ldots, N_p \]  

(14)

\[ P_{gu,min} \leq P_{gu} \leq P_{gu,max} \quad u = 1, \ldots, N_p \]  

(15)

\[ Q_{gu,min} \leq Q_{gu} \leq Q_{gu,max} \quad u = 1, \ldots, N_p \]  

(16)

\[ H_{hj}^{min} \leq H_{hj} \leq H_{hj}^{max} \quad j = 1, 2, \ldots, n_h \]  

(17)

\[ P_{ck,min}(H_{ck}) \leq P_{ck} \leq P_{ck}^{max}(H_{ck}) \quad k = 1, 2, \ldots, n_c \]  

(18)

\[ H_{ck}^{min}(P_{ck}) \leq H_{ck} \leq H_{ck}^{max}(P_{ck}) \quad k = 1, 2, \ldots, n_c \]  

(19)

where \( P_{ck}(H_{ck}), P_{ck}^{max}(H_{ck}), H_{ck}^{min}(P_{ck}) \) and \( H_{ck}^{max}(P_{ck}) \) are the inequalities which specify the feasible operating region (FOR) of the cogeneration unit \( k \).

4) TRANSFORMER TAP SETTING CONSTRAINTS

\[ T_{S_i}^{min} \leq T_{S_i} \leq T_{S_i}^{max} \quad j = 1, \ldots, n_T \]  

(20)

5) CONSTRAINTS OF SHUNT COMPENSATOR

\[ Q_{C_i}^{min} \leq Q_{C_i} \leq Q_{C_i}^{max} \quad i = 1, \ldots, n_C \]  

(21)

6) SECURITY CONSTRAINTS

\[ V_{L_{min}} \leq V_{L_{m}} \leq V_{L_{max}} \quad m = 1, \ldots, n_L \]  

(22)

\[ S_{lr} \leq S_{lr}^{max} \quad r = 1, \ldots, n_r \]  

(23)

F. OPTIMIZATION PROBLEM
To solve the above objective functions in this paper, they are combined and converted into a single objective function by using weighting factors as follows [6], [26]:

\[ \min F = F_p + F_h + F_c + \sum_{d=1}^{n_w} C_{w,d}(P_{ws,d}) + C_{pe,d}(P_{wav,d} - P_{ws,d}) + C_{rw,d}(P_{ws,d} - P_{wav,d}) \]

\[ + w_1 \times P_L + w_2 \times VD \]  

(24)

These weighting factors are suitable values chosen by the user to balance the different objective functions [6], [7], [26], [27].

One of the trusted methods of handling the inequality constraints for any optimization problem is employing the penalty factor. The penalty factors are large positive numbers defined by the user to decline the unfeasible solutions [6], [7], [26], [27]. In this paper, the constrained optimization problem is converted into an unconstrained
problem using penalty functions as follows [26]:

\[
\begin{align*}
\min F &= F_p + F_h + F_c + \sum_{d=1}^{n_w} (C_w,d(P_{w,d}) \\
&+ C_{pw,d}(P_{waw,d} - P_{w,d}) \\
&+ C_{rw,d}(P_{rw,d} - P_{waw,d})) \\
&+ w_1 \times P_L + w_2 \times VD + \tau_p(P_{g1} - P_{g1}^{lim})^2 \\
&+ \tau_v \sum_{m=1}^{n_g} (V_{Li} - V_{Li}^{lim})^2 + \tau_q \sum_{i=1}^{n_g} (Q_{gi} - Q_{gi}^{lim})^2 \\
&+ \tau_s \sum_{r=1}^{n_c} (S_{lr} - S_{lr}^{max})^2 + \tau_h \sum_{k=1}^{n_c} (H_{ck} - H_{ck}^{lim})^2 \\
&+ \tau_{hh} \sum_{j=1}^{n_c} (H_{bj} - H_{bj}^{lim})^2
\end{align*}
\]

(25)

The limit values of the variables \( P_{g1}, V_L, Q_R, H_c, \) and \( H_h \) can be expressed as follows:

\[
Y^{lim} = \begin{cases} 
 cc^{Y^{max}} & Y > Y^{max} \\
 Y^{min} & Y < Y^{min}
\end{cases}
\]

(26)

where \( Y^{lim} \) represents \( P_{g1}^{lim}, V_L^{lim}, Q_R^{lim}, H_c^{lim}, \) or \( H_h^{lim} \).

### III. STOCHASTIC WIND POWER AND UNCERTAINTY MODELS

The wind speed is a random variable where its distribution can be better defined by Weibull probability density function (PDF) with shape factor \( (k) \) and scale factor \( (c) \). The PDF of the wind speed is defined as [9], [25]:

\[
PDF(S; k, c) = \frac{k}{c} \left( \frac{S}{c} \right)^{k-1} \times e^{-\left( \frac{S}{c} \right)^k} \quad 0 < S < \infty
\]

(27)

### A. WIND POWER MODEL

The output wind power from a wind turbine is a function of wind speed and can be expressed as follows:

\[
P_w(S) = \begin{cases} 
 0 & \text{for } S < S_{in} \text{ and } S > S_{out} \\
 P_{wr} \left( \frac{S - S_{in}}{S_{r} - S_{in}} \right) & \text{for } S_{in} \leq S \leq S_{r} \\
 P_{wr} & \text{for } S_{r} < S \leq S_{out}
\end{cases}
\]

(28)

### B. WIND POWER PROBABILITIES FOR DIFFERENT WIND SPEEDS

From (28), one can note that if \( S \) is below \( S_{in} \) and above \( S_{out} \), the power output is zero. Also, the wind turbine produces \( P_{wr} \) between \( S_{r} \) and \( S_{out} \). For these discrete zones, probabilities can be described as follows [28]:

\[
\begin{align*}
&f_w(P_w|P_w = 0) = 1 - \exp \left( -(S_{in}/c)^k \right) + \exp \left( -(S_{out}/c)^k \right) \\
&f_w(P_w|P_w = P_{wr}) = \exp \left( -(S_{r}/c)^k \right) - \exp \left( -(S_{out}/c)^k \right)
\end{align*}
\]

(29)

On contrary to the above discrete zones, the output wind power is continuous between \( S_{in} \) and \( S_{r} \) of wind. Therefore, the probability for this zone can be expressed as follows [28]:

\[
f_w(P_w) = \frac{k(S_r - S_{in})}{c^k} \times P_{wr} \left( \frac{S_{in} + P_w}{P_{wr} (S_r - S_{in})} \right)^{k-1} \times \exp \left( \frac{(S_{in} + P_w - P_{wr})(S_r - S_{in})}{c} \right)
\]

(31)

### IV. PROPOSED OPTIMIZATION ALGORITHM

#### A. MOTH SWARM ALGORITHM OVERVIEW

Moth swarm algorithm (MSA) is proposed based on the behavior of a group of moths while searching food in the dark. In MSA, the light source position represents the search space to the optimization problem. In addition, the light source’s brightness is considered as the fitness of the possible solution. Moreover, the moths are divided into three groups [7].

The first group (pathfinders) is a small group used to explore the new area in the search space for the solution by finding the best position of the light source and lead other members in the population to this position. The second group (prospectors) walks in a random spiral path around the light source found by the first group. The third group (onlookers) fly towards the best solution determined by the second group [7]. The four main phases of MSA can be summarized as follows:

1) INITIALIZATION PHASE

In this phase, the position of each moth is randomly initialized for the \( m \)-dimensional problem and \( z \) number of population as follows [7]:

\[
x_{ij} = x_{ij}^{min} + \text{rand}[0,1] \times (x_{ij}^{max} - x_{ij}^{min})
\]

(32)

where \( i \in \{1, 2, \ldots, z\}, j \in \{1, 2, \ldots, m\} \) and \( \text{rand}[0,1] \) is a random number between 0 and 1.

Henceforward, the moths are arranged in ascending order according to their fitness. The moths with best fitnesses are selected as pathfinder moths. The moths with second best and worst fitnesses are selected to be the prospectors and onlookers, respectively.

2) RECONNAISSANCE PHASE

In this phase, the pathfinders’ positions are updated in five steps. The diversity index for the crossover points is employed in the first step as follows:

\[
\sigma^H_j = Y \left( \frac{1}{z^2} \sum_{i=1}^{z} \left( x_{ij} - \frac{1}{z} \sum_{i=1}^{z} x_{ij} \right)^2 \right)
\]

(33)

\[
\mu^H = \frac{1}{m} \sum_{j=1}^{m} \sigma^H_j
\]

(34)

In the second step, Lévy flights is used. While in the third step, the sub-trial vectors are created based on host and donor vectors. After that, the proposed adaptive crossover operation
based on population diversity is employed in the fourth step to update the position of each moth in the pathfinder group. In the final step, the selection strategy is applied to choosing the fittest solutions at the next iteration [19]. All details of these five steps can be found in [7].

3) TRANSVERSE ORIENTATION PHASE

In this phase. The number of prospectors is reduced with the iteration as follows [7]:

\[ z_{pr} = \text{round}((z - z_f) \times (1 - it/\max it)) \]  (35)

After that, each prospector’s position is updated for the next iteration with respect to the spiral light path as follows [7]:

\[ x_i^{it+1} = |x_i^{it} + x_p^{it}| \cdot e^\theta \cdot \cos(2\pi \theta) + x_p^{it} \]  (36)

where \( i \in \{1, 2, \ldots, z_{pr}\} \), \( \theta \in [-1 - it/\max it, 1] \) is a random value which used to define the spiral shape.

4) CELESTIAL NAVIGATION PHASE

By reducing the number of prospectors with iteration, the number of onlookers increases in the search space. The onlooker group tries to find the most proposing area. Therefore, the onlookers are divided into two parts. The first one with size \( z_g = \text{round}(z - z_f - z_{pr}/2) \) use Gaussian stochastic distribution to navigate the promising places as follows [7], [20]:

\[ x_i^{it+1} = x_i^{it} + \kappa_1 + [\kappa_2 \times \text{best}_g^{it} - \kappa_3 \times x_i^{it}] \]  (37)

where \( i \in \{1, 2, \ldots, z_g\} \).

The second part of onlookers (\( z_a \)) moves towards the light source based on the associative learning mechanism with an immediate memory to imitate the actual behavior of moths in nature. The new onlookers for the next generation can be obtained as follows [7], [20].

\[ x_i^{it+1} = x_i^{it} + 0.001 \times G[x_i^{it} - x_i^{\text{min}}, x_i^{\text{max}} - x_i^{it}] + r_1 \times (1 - \frac{it}{\max it}) \times (\text{best}_p^{it} - x_i^{it}) + 2 \times \frac{it}{\max it} \times r_2 \times (\text{best}_g^{it} - x_i^{it}) \]  (38)

where \( i \in \{1, 2, \ldots, z_a\} \).

All details and the flowchart of the MSA can be found in [7].

B. MODIFIED MOTH SWARM ALGORITHM (MMSA)

The MMSA is proposed in this paper to improve the convergence speed, the performance and the efficiency of the conventional MSA. In conventional MSA, the number of prospectors (\( z_{pr} \)) is reduced with the iteration according to (35). This technique has an exploratory effect but it reduces the convergence speed of the conventional MSA. Therefore, equation (35) is modified in the proposed MMSA in this paper to increase the exploration-exploitation balance and convergence speed of the conventional MSA as follows:

\[ z_{pr} = \text{round}((z - z_f) \times \exp(-\left(\frac{it}{\max it/4}\right))) \]  (39)

In addition, the associative learning mechanism with immediate memory (38) is modified in the proposed MMSA by modifying the social and cognitive factors as follows:

\[ x_i^{it+1} = x_i^{it} + 0.001 \times G[x_i^{it} - x_i^{\text{min}}, x_i^{\text{max}} - x_i^{it}] + r_1 \times \exp(-2 * g/G) \times (\text{best}_p^{it} - x_i^{it}) + \exp(-(1 - (2 * g/G))) \times r_2 \times (\text{best}_g^{it} - x_i^{it}) \]  (40)

Modifying the strategy of reducing the number of prospectors with iteration and the associative learning mechanism with immediate memory not only maintain the exploratory feature but also accelerate the convergence of the algorithm. Also, the performance and efficiency of conventional MSA are enhanced by employing these modifications.

The implementation of the proposed MMSA to solve the OPF problem can be summarized as follows:

Step 1: Define the system data.
Step 2: Define the parameters of the proposed MMSA including the maximum number of iterations, population size and the number of pathfinders.
Step 3: Run initial power flow to obtain the base case solution.
Step 4: Randomly initialize the first population of moths’ positions using (32).
Step 5: Run power flow for each member in the population and calculate the fitness (value of the objective function (25)) of each moth in the population.
Step 6: Identify the type of each moth. According to the value of the objective function, chose the first best moths as pathfinders. Then select the second best as prospectors. While the worst moths are selected as onlookers.
Step 7: Update the moths’ position as follows: i.

1) The pathfinders’ positions can be updated as described in subsection IV-A.2.
2) The number of prospectors is reduced with the iteration using the modified strategy (39).
3) The first group of onlookers moves with Gaussian walks using (37). While the second group moves with the modified associative learning mechanism with immediate memory (40).

Step 8: Run power flow for each updated moth in the population. Then calculate the new fitness (value of the objective function (25)) of each updated moth.
Step 9: Repeat steps 6 to 8 until the stopping criterion is achieved.
Step 10: The best pathfinder in the last iteration and its fitness (value of the objective function) represent the optimal solution.

V. SIMULATION RESULTS

To demonstrate the effectiveness and feasibility of the proposed MMSA in solving the OPF problem of combined heat and power system incorporating stochastic wind power,
the MMSA is tested using modified IEEE 30-bus system and modified IEEE 118-bus system. In the implementation of MMSA, some parameters should be determined first to get the optimal solution. In this paper, the values of these parameters are selected using empirical tests by running the MMSA several times with different combinations of these parameters. To calculate the values of Weibull shape \( k \) and scale \( c \) parameters the historic data of wind speed is adopted from NREL [29]. To investigate the superiority of the proposed MMSA with recently published methods, its performance is compared with conventional MSA [7], improved gray wolf optimizer (IGWO) [23] and TLBO [30].

The weighting factors \( w_1 \) and \( w_2 \) are chosen as 1950 and 200, respectively for both test systems [27]. While, the penalty factors \( \tau_p \), \( \tau_q \), \( \tau_v \), \( \tau_s \), \( \tau_{hc} \), and \( \tau_{hc} \) are selected in this work as \( 10^6 \), \( 10^6 \), \( 10^4 \), \( 10^4 \), \( 10^3 \) and \( 10^3 \), respectively for both test systems [27]. All the numerical studies have been run on 2.8-GHz i7 PC with 16 GB of RAM using MATLAB 2017b.

**A. TEST SYSTEM 1**

This system is based on the standard IEEE-30 bus system which has 6 power only generators [31]. The limits of voltage magnitude \( \in [0.95, 1.06] \) for the slack bus and \( \in [0.95, 1.05] \) for the remaining buses. Also, \( Q_C \in [0, 0.05] \) for the remaining buses. Furthermore, bus 1 is chosen as the slack bus.

This system is modified in this paper to accommodate 3 cogeneration units, 1 wind farm, and 1 heat only unit. The power only generators at buses 5, 8 and 11 are replaced by 3 cogeneration units. Also, 1 heat only unit is installed at 31 which is used out of the IEEE 30-bus to only supply the demand of heat. The data of the cogeneration and heat only units are extracted from [2]. The generator at bus 13 is replaced by a wind farm with reactive power capability. The wind farm has total power equal to 60 MW. The parameters of wind turbines are: \( c = 10 \), \( k = 2 \), \( g_d = 1.3 \), \( g_p = 1 \) and \( g_r = 4 \). The valve point effect is only considered for the power only generators at buses 1 and 2.

1) CASE 1

The aim of this case is to investigate the effect of wind parameters on the cost using the proposed MMSA.

**a: EFFECT OF SCHEDULED WIND POWER ON TOTAL WIND COST**

The scheduled wind power is varied from 0 to \( P_{wr} \) and the reserve, penalty, direct and total wind costs are calculated. Total wind cost is the sum of direct, reserve and penalty costs. Figure 1 shows the variation of different components of wind power cost with the scheduled wind power.

The results show that, as the scheduled wind power increases, the direct cost increases linearly. Also, larger spinning reserve is essential which leads to increase the reserve cost. In addition, the penalty cost rightly decreases. As a result, the total wind cost increases.

**b: EFFECT OF SCALE PARAMETER (C) ON TOTAL WIND COST**

To show the effect of the scale parameter \( c \) of PDF, \( c \) will be varied from 2 to 16 while keeping \( k \) and \( P_{ws} \) constant. \( P_{ws} \) is fixed at 20 MW. The assumption of \( P_{ws} \) is sensible as the capacity factor for the practical wind farms varies between 30% to 45% [9]. Figure 2 shows the variation of different components of wind power cost with the scale parameter.

It can be noticed from Fig. 2 that, by increasing the scale parameter, higher wind speeds prevail which increases the output wind power rapidly. This leads to increasing of penalty cost and decreasing of reserve cost with scheduled power remaining the same. This, in turn, raises the total wind cost.
FIGURE 3. Variation of different costs with (a) reserve cost coefficient and (b) penalty cost coefficient.

Table 1. Optimal Values of Control Variables of Case 2.

<table>
<thead>
<tr>
<th>Variable</th>
<th>TLBO</th>
<th>IGWO</th>
<th>MSA</th>
<th>MMSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{G1}$ (MW)</td>
<td>50.450</td>
<td>96.0726</td>
<td>57.0175</td>
<td>84.7741</td>
</tr>
<tr>
<td>$P_{G2}$ (MW)</td>
<td>79.2235</td>
<td>21.9689</td>
<td>65.6327</td>
<td>23.4176</td>
</tr>
<tr>
<td>$P_{G3}$ (MW)</td>
<td>32.4443</td>
<td>45.0441</td>
<td>40.3819</td>
<td>45.0347</td>
</tr>
<tr>
<td>$P_{G4}$ (MW)</td>
<td>43.5627</td>
<td>45.2531</td>
<td>45.6700</td>
<td>45.0357</td>
</tr>
<tr>
<td>$P_{G11}$ (MW)</td>
<td>38.7487</td>
<td>44.9868</td>
<td>45.1034</td>
<td>44.7834</td>
</tr>
<tr>
<td>$P_{G12}$ (MW)</td>
<td>43.2396</td>
<td>34.2761</td>
<td>33.2897</td>
<td>44.0275</td>
</tr>
<tr>
<td>$V_1$ (p.u.)</td>
<td>1.0548</td>
<td>1.0195</td>
<td>1.0570</td>
<td>1.0184</td>
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<tr>
<td>$V_2$ (p.u.)</td>
<td>1.0494</td>
<td>1.0022</td>
<td>1.0427</td>
<td>1.0091</td>
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<tr>
<td>$V_5$ (p.u.)</td>
<td>1.0143</td>
<td>0.9920</td>
<td>0.9846</td>
<td>0.9864</td>
</tr>
<tr>
<td>$V_6$ (p.u.)</td>
<td>1.0067</td>
<td>0.9787</td>
<td>1.0158</td>
<td>1.0038</td>
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<tr>
<td>$V_{11}$ (p.u.)</td>
<td>1.0609</td>
<td>1.0313</td>
<td>1.0221</td>
<td>1.0177</td>
</tr>
<tr>
<td>$V_{12}$ (p.u.)</td>
<td>0.9908</td>
<td>1.0047</td>
<td>1.0180</td>
<td>1.0042</td>
</tr>
<tr>
<td>$T_{11}$ (6-9)</td>
<td>1.0454</td>
<td>0.9569</td>
<td>0.9478</td>
<td>1.0183</td>
</tr>
<tr>
<td>$T_{12}$ (6-10)</td>
<td>1.0483</td>
<td>0.9487</td>
<td>1.0266</td>
<td>0.9306</td>
</tr>
<tr>
<td>$T_{13}$ (4-12)</td>
<td>0.9846</td>
<td>0.9510</td>
<td>1.0235</td>
<td>0.9521</td>
</tr>
<tr>
<td>$T_{36}$ (28-27)</td>
<td>0.9281</td>
<td>0.9111</td>
<td>0.9776</td>
<td>0.9357</td>
</tr>
<tr>
<td>$Q_{c10}$ (MVAR)</td>
<td>4.9728</td>
<td>1.1784</td>
<td>4.8458</td>
<td>5.0000</td>
</tr>
<tr>
<td>$Q_{c12}$ (MVAR)</td>
<td>2.3871</td>
<td>1.7841</td>
<td>3.7248</td>
<td>5.0000</td>
</tr>
<tr>
<td>$Q_{c15}$ (MVAR)</td>
<td>3.7078</td>
<td>4.4300</td>
<td>3.6501</td>
<td>4.6585</td>
</tr>
<tr>
<td>$Q_{c17}$ (MVAR)</td>
<td>4.9864</td>
<td>4.9548</td>
<td>3.1137</td>
<td>0.0000</td>
</tr>
<tr>
<td>$Q_{c20}$ (MVAR)</td>
<td>4.2618</td>
<td>4.7764</td>
<td>4.2017</td>
<td>4.8536</td>
</tr>
<tr>
<td>$Q_{c21}$ (MVAR)</td>
<td>4.9612</td>
<td>1.6307</td>
<td>3.0832</td>
<td>2.8191</td>
</tr>
<tr>
<td>$Q_{c23}$ (MVAR)</td>
<td>3.7655</td>
<td>3.9192</td>
<td>4.9309</td>
<td>0.0000</td>
</tr>
<tr>
<td>$Q_{c24}$ (MVAR)</td>
<td>2.5328</td>
<td>3.2522</td>
<td>4.2395</td>
<td>4.5702</td>
</tr>
<tr>
<td>$Q_{c29}$ (MVAR)</td>
<td>4.5463</td>
<td>0.0000</td>
<td>3.1175</td>
<td>1.2956</td>
</tr>
<tr>
<td>$H_{15}$ (MWh)</td>
<td>46.4078</td>
<td>54.6385</td>
<td>52.5843</td>
<td>53.7199</td>
</tr>
<tr>
<td>$H_{8}$ (MWh)</td>
<td>53.7441</td>
<td>53.8731</td>
<td>50.8986</td>
<td>54.7780</td>
</tr>
<tr>
<td>$H_{11}$ (MWh)</td>
<td>52.2553</td>
<td>54.8621</td>
<td>52.9379</td>
<td>54.8274</td>
</tr>
<tr>
<td>$H_{31}$ (MWh)</td>
<td>22.5928</td>
<td>11.6263</td>
<td>18.5792</td>
<td>11.6748</td>
</tr>
</tbody>
</table>

Table 2. Results of All Methods for Case 2.

<table>
<thead>
<tr>
<th>Method</th>
<th>TLBO</th>
<th>IGWO</th>
<th>MSA</th>
<th>MMSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Operating Cost ($/h)</td>
<td>9419.57</td>
<td>9321.87</td>
<td>9362.04</td>
<td>9323.78</td>
</tr>
<tr>
<td>Power loss (MW)</td>
<td>4.27</td>
<td>4.20</td>
<td>3.69</td>
<td>3.67</td>
</tr>
<tr>
<td>Voltage deviation (p.u.)</td>
<td>0.45</td>
<td>0.22</td>
<td>0.21</td>
<td>0.15</td>
</tr>
<tr>
<td>Objective function ($/h)</td>
<td>9643.39</td>
<td>9460.91</td>
<td>9510.49</td>
<td>9439.04</td>
</tr>
</tbody>
</table>

The results show that the MMSA gives better objective function than other methods without any violation of any constraint. The objective function of MMSA is $9439.04$/h. By employing the MMSA, the objective function of TLBO,
IGWO, and MSA are decreased by 204.34$/h, 21.87$/h and 71.45$/h, respectively which demonstrates the effectiveness of MMSA. Figure 5 shows that all voltages are within their limits. Also, the voltage deviation and power loss of MMSA are lower than other methods.

3) CASE3
This case investigates the effectiveness of MMSA to solve the OPF of combined heat and power system considering stochastic wind power under contingency state. The outage of lines (10-17) and (10-21) simulates the contingency state in this case. The optimal values of the control variables of this case are given in Table 3. Table 4, Fig. 6 and Fig. 7 show the results of MMSA and other methods.

The results show that the MMSA gives better objective function than other methods under contingency state without any violation of any constraint. It can be noted that the proposed MMSA reduces the objective function of TLBO, IGWO, and MSA by 172.63$/h, 112.89$/h and 150.69$/h, respectively which prove the effectiveness of MMSA over other methods in the contingency state. Figure 7 shows that the bus voltages are within the upper and lower limits. The voltage deviation of MMSA is lower than other methods.

B. TEST SYSTEM 2
A large test system is implemented in this case to prove the scalability and suitability of the MMSA for large-scale systems. This system is based on the standard IEEE-118 bus system which has 54 power only generators [32]. The limits of voltage magnitude ∈ [0.94, 1.06]p.u. for all buses. Also, $Q_C \in [0, 0.3]p.u.$ and $Q_L = 0$. The power only generation at buses 12, 31, 54, 87, 103 and 111 are replaced by 6 cogeneration units. Also, 1 heat only unit is installed at bus 119 which is used out of the IEEE 118 bus to only supply the demand of heat. The data of the cogeneration and heat only units are extracted from [2]. In addition, the power only generators at buses 36 and 49 are replaced by wind farms with reactive power capability. The first and second wind farm has total output power equal to 400 MW and 600 MW, respectively. The parameters of wind turbines for both wind farms are: $c_1 = 10$, $c_2 = 9$, $k_1 = k_2 = 2$, $g_{d1} = 1.3$, $g_{d2} = 1.6$, $g_{p1} = 1$, $g_{p2} = 1.5$, $g_{r1} = 4$ and $g_{r2} = 3$.

1) CASE 4
The objective of this case study is the minimization of the total operating cost of different generator units (power, heat, cogeneration and wind units) while the two objective functions of power loss and voltage deviation are neglected. Table 5 shows the results of the MMSA method and other methods. The results show that the MMSA outperforms other methods in the large-scale system. The proposed MMSA reduces the total operating cost of TLBO, IGWO, and MSA by 5593.86$/h, 488.08$/h, and 2003.23$/h, respectively which prove the effectiveness of the MMSA over other methods in the large-scale power system. Also, Table 5 shows the total operating cost improvements of the proposed MMSA over other methods.
C. DISCUSSION

The results of the MMSA method are compared with TLBO, IGWO and MSA methods for different cases and systems. These comparisons are shown in Tables 1-5 and Figures 4-7. These results prove that the proposed MMSA outperforms other methods not only in the normal state but also in contingency state. Also, the results show the effectiveness of MMSA method over other methods in large-scale systems.

Moreover, Figure 8 shows the convergence characteristics of all methods for case 2, case 3 and case 4. These figures indicate that the objective function of the proposed MMSA method converges smoothly to the best solution in all cases without any oscillations which proves the convergence reliability of the MMSA. In addition, the MMSA reaches to the optimal solution faster than the conventional MSA. This is the result of the modifications used to derive the MMSA.

To evaluate the robustness of the MMSA a statistical test is conducted where 30 independent runs are carried out for case 2, case 3 and case 4. The best, the mean, the worst
and relative standard deviation (RSD) values of the proposed MMSA are tabulated in Table 6. One can notice that the best, the mean and the worst values of the objective function obtained by the MMSA are very close which reveals the ability of the MMSA to reach either to the optimal solution or very near to it in each run.

The computational time of MMSA and other methods for case 2, case 3 and case 4 are tabulated in Table 7.


TABLE 3. Optimal Values of Control Variables of Case 3.

<table>
<thead>
<tr>
<th>Control Variable</th>
<th>TLBO</th>
<th>IGWO</th>
<th>MSA</th>
<th>MMSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>P_G1 (MW)</td>
<td>50.5763</td>
<td>54.3676</td>
<td>50.9822</td>
<td>87.2983</td>
</tr>
<tr>
<td>P_G2 (MW)</td>
<td>70.5579</td>
<td>78.0824</td>
<td>73.5389</td>
<td>20.0000</td>
</tr>
<tr>
<td>P_G3 (MW)</td>
<td>30.3773</td>
<td>36.6862</td>
<td>42.7950</td>
<td>44.9683</td>
</tr>
<tr>
<td>P_G4 (MW)</td>
<td>42.4501</td>
<td>44.1063</td>
<td>41.5826</td>
<td>45.0291</td>
</tr>
<tr>
<td>P_G11 (MW)</td>
<td>38.5765</td>
<td>39.9871</td>
<td>39.3532</td>
<td>45.1107</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control Variable</th>
<th>TLBO</th>
<th>IGWO</th>
<th>MSA</th>
<th>MMSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>V_1 (p.u.)</td>
<td>1.0574</td>
<td>1.0594</td>
<td>1.0585</td>
<td>1.0585</td>
</tr>
<tr>
<td>V_2 (p.u.)</td>
<td>1.0477</td>
<td>1.0498</td>
<td>1.0491</td>
<td>1.0471</td>
</tr>
<tr>
<td>V_3 (p.u.)</td>
<td>1.0336</td>
<td>1.0399</td>
<td>1.0180</td>
<td>1.0250</td>
</tr>
<tr>
<td>V_4 (p.u.)</td>
<td>1.0486</td>
<td>1.0424</td>
<td>1.0468</td>
<td>1.0500</td>
</tr>
<tr>
<td>V_5 (p.u.)</td>
<td>1.0490</td>
<td>1.0496</td>
<td>1.0483</td>
<td>1.0500</td>
</tr>
<tr>
<td>V_6 (p.u.)</td>
<td>1.0317</td>
<td>1.0396</td>
<td>1.0491</td>
<td>1.0079</td>
</tr>
<tr>
<td>T_11 (6-9)</td>
<td>1.0011</td>
<td>1.0971</td>
<td>1.0708</td>
<td>1.0898</td>
</tr>
<tr>
<td>T_12 (6-10)</td>
<td>1.0701</td>
<td>1.0026</td>
<td>1.0272</td>
<td>0.9013</td>
</tr>
<tr>
<td>T_16 (4-12)</td>
<td>1.0365</td>
<td>1.0128</td>
<td>1.0207</td>
<td>0.9841</td>
</tr>
<tr>
<td>T_36 (28-27)</td>
<td>0.9696</td>
<td>1.0134</td>
<td>1.0591</td>
<td>0.9000</td>
</tr>
<tr>
<td>Q_c10 (MVAr)</td>
<td>4.1212</td>
<td>4.8428</td>
<td>4.8597</td>
<td>4.9978</td>
</tr>
<tr>
<td>Q_c12 (MVAr)</td>
<td>2.5916</td>
<td>4.9024</td>
<td>4.4468</td>
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</tr>
<tr>
<td>Q_c15 (MVAr)</td>
<td>4.4748</td>
<td>4.8662</td>
<td>4.6693</td>
<td>1.8857</td>
</tr>
<tr>
<td>Q_c17 (MVAr)</td>
<td>4.9132</td>
<td>4.9093</td>
<td>3.9847</td>
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<td>Q_c20 (MVAr)</td>
<td>4.5634</td>
<td>4.9020</td>
<td>4.8130</td>
<td>0.0000</td>
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<tr>
<td>Q_c21 (MVAr)</td>
<td>4.6249</td>
<td>4.9637</td>
<td>4.7695</td>
<td>4.9997</td>
</tr>
<tr>
<td>Q_c23 (MVAr)</td>
<td>4.9542</td>
<td>4.9142</td>
<td>4.8200</td>
<td>5.0000</td>
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<tr>
<td>Q_c24 (MVAr)</td>
<td>4.7940</td>
<td>4.8882</td>
<td>4.5700</td>
<td>5.0000</td>
</tr>
<tr>
<td>Q_c29 (MVAr)</td>
<td>4.7242</td>
<td>4.9579</td>
<td>4.3645</td>
<td>4.9983</td>
</tr>
<tr>
<td>H_1 (MWh)</td>
<td>46.2892</td>
<td>51.0757</td>
<td>52.7139</td>
<td>54.9408</td>
</tr>
<tr>
<td>H_6 (MWh)</td>
<td>52.0989</td>
<td>53.8125</td>
<td>53.3757</td>
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</tr>
<tr>
<td>H_11 (MWh)</td>
<td>43.8486</td>
<td>52.2774</td>
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<tr>
<td>H_31 (MWh)</td>
<td>32.7633</td>
<td>17.8344</td>
<td>29.1928</td>
<td>10.6092</td>
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</table>

TABLE 4. Results of All Methods for Case 3.

<table>
<thead>
<tr>
<th>Case</th>
<th>TLBO</th>
<th>IGWO</th>
<th>MSA</th>
<th>MMSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 2</td>
<td>9439.04</td>
<td>9451.59</td>
<td>9468.01</td>
<td>0.07</td>
</tr>
<tr>
<td>Case 3</td>
<td>9505.18</td>
<td>9520.21</td>
<td>9538.01</td>
<td>0.10</td>
</tr>
<tr>
<td>Case 4</td>
<td>118981.13</td>
<td>119857.32</td>
<td>120821.24</td>
<td>0.48</td>
</tr>
</tbody>
</table>

TABLE 5. Results of All Methods for Case 4.

<table>
<thead>
<tr>
<th>Method</th>
<th>Total operating cost ($/h)</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>MMSA</td>
<td>118981.13</td>
<td>–</td>
</tr>
<tr>
<td>TLBO</td>
<td>124574.98</td>
<td>4.49%</td>
</tr>
<tr>
<td>IGWO</td>
<td>119469.21</td>
<td>0.41%</td>
</tr>
<tr>
<td>MSA</td>
<td>120984.36</td>
<td>1.66%</td>
</tr>
</tbody>
</table>

The computational time of the MMSA is lower than other methods in all cases which proves the efficiency of the proposed MMSA over other methods regarding the computational time. All these results and comparisons clearly show the superiority of the MMSA over other methods not only in small-scale systems but also in large scale systems which makes it possible to employ the proposed MMSA to get the optimal solution of the real-life systems.

VI. CONCLUSION

In this paper, an introductory formulation of OPF problem of combined heat and power system incorporating stochastic wind power is presented. Also, a modified moth swarm algorithm (MMSA) is proposed to improve the convergence speed, the performance and the efficiency of the conventional MMSA. The proposed MMSA is then employed to solve the OPF problem of combined heat and power system incorporating stochastic wind power using two test systems. Also, the scalability of the MMSA is tested using a large-scale test system. The results revealed that the MMSA significantly outperformed TLBO, IGWO and MSA methods in the normal and contingency conditions whatever the size of the system. This gives the proposed MMSA the ability to solve real-life applications.

REFERENCES


