



A Modified Honey Badger Algorithm for Solving Optimal Power Flow Optimization Problem

Shaymah Akram Yasear^{1*} Hayder M. A. Ghanimi²

Department of Biomedical Engineering, Al-Mustaqbal University College, Hillah, Babylon, 51001, Iraq

Department of Biomedical Engineering, University of Warith Al-Anbiyaa, Karbala, 56001, Iraq

* Corresponding author's Email: hayder.alghanami@uowa.edu.iq

Abstract: This paper proposes a modified honey badger algorithm (MHBA) for solving the optimal power flow (OPF) problem. This problem is a highly non-linear, non-convex and complex optimization problem with several decision variables and constraints. The original honey badger algorithm (HBA) has the problem of trapping in local optima due to the loss of population diversity, especially in solving complex optimization problems. Therefore, the MHBA aims at sufficient improvement in finding the optimal solution and feasibility. Opposition-based learning strategy (OBL) is integrated with the MHBA to preserve the diversity of the population and enhance the convergence toward the optimal solution. The effectiveness of the MHBA algorithm is evaluated on five objective functions of the OPF problem namely, total generation fuel cost minimization, active power and reactive power transmission losses minimization, voltage deviation and voltage stability enhancement. The performance of the proposed algorithm is tested and validated on the IEEE 30-bus test system. The proposed MHBA is compared with the HBA and other nature-inspired optimization algorithms reported in the literature. The results indicate that the proposed MHBA algorithm has the superiority to jump out of the local optimal and better convergence in solving the OPF problem. This is due to the strategy used in the algorithm which helps in maintaining the population diversity and provides a proper balance between exploration and exploitation.

Keywords: Global optimization, Swarm intelligence, Nature-inspired algorithms, Optimization problem, Metaheuristic.

1. Introduction

The optimal power flow (OPF) problem of a power system studies the optimal power flow distribution that satisfies a given load and follows various operating constraints under the premise of a specific power grid structure. The constant increase in the demand for electrical energy has been a great challenge to the prevailing networks, to provide power to the consumer through an economically and efficient system. Therefore, solving the OPF problem is most important to assess the quality of the power system. The best operating condition of a power system can be achieved by adjusting the parameters of various control devices with respect to the constraints of a network [1].

Several deterministic methods have been employed to solve the OPF problem with different

objective functions, such as sequential quadratic programming, the simplex method, the interior point method and the Newton method [2]. However, the OPF is a highly non-linear, non-convex and complex optimization problem with several decision variables and constraints thus the deterministic methods fail to solve the OPF problem in a reasonable time.

Metaheuristics are approximate methods applicable to various optimization problems [3, 4]. Many metaheuristics are inspired by natural phenomena, such as evolution theory, the collective behaviour of groups of animals, the laws of physics or the behaviour and lifestyle of human beings. Examples of these algorithms include particle swarm optimization (PSO) [5], ant colony optimization (ACO) [6], firefly algorithm (FA) [7], artificial bee colony (ABC) [8], grey wolf optimizer (GWO) [9],

Table 1. Nature-inspired algorithms employed for solving the OPF problem

| Algorithm | FC | APL | RPL | VD | L _{max} |
|-----------|----|-----|-----|----|------------------|
| ABC [18] | √ | - | - | - | - |
| PSO [19] | √ | - | - | - | - |
| PSO [20] | √ | - | - | - | - |
| PSO [21] | √ | - | - | - | - |
| GWO [22] | √ | √ | √ | - | - |
| DE [22] | √ | √ | √ | - | - |
| HHO [23] | √ | √ | - | - | - |
| SSA [24] | √ | √ | - | - | - |
| MFO [25] | √ | √ | - | - | - |
| PSO [26] | √ | - | - | √ | √ |
| BBO [27] | √ | - | - | √ | √ |
| GSA [28] | √ | - | - | √ | √ |
| SSA [29] | √ | √ | - | √ | - |
| MBO [30] | √ | √ | - | √ | - |
| HHO [31] | √ | √ | - | √ | - |
| MVO [31] | √ | √ | - | √ | - |
| GOA [31] | √ | √ | - | √ | - |
| ABC [33] | √ | √ | - | √ | √ |
| FA [32] | √ | √ | - | √ | √ |
| DA [32] | √ | √ | - | √ | √ |
| ESCA [35] | √ | √ | - | √ | √ |
| MSA [32] | √ | √ | - | √ | √ |
| DSA [34] | √ | √ | - | √ | √ |
| WOA [36] | √ | √ | - | - | - |
| SCA [38] | √ | √ | - | √ | - |
| MSCA [38] | √ | √ | - | √ | - |
| EGA [37] | √ | √ | - | - | √ |
| BHBO [39] | √ | √ | √ | √ | √ |
| GWO [41] | √ | √ | √ | √ | √ |

Harris hawk algorithm (HHO) [10]. Other metaheuristics have been developed based on the physical system, such as the gravitational search algorithm (GSA) [11] and Henry gas solubility optimization (HGSO) [12]. It is worth mentioning that there are several other non-nature inspired metaheuristics proposed in the literature, such as [13-16]. however, this paper focuses on nature-inspired algorithms, which have shown superior skills in solving various optimization problems [17].

Many nature-inspired algorithms have been employed to solve the OPF problem with various objective functions of the power system. In [18] an ABC algorithm has been applied to reduce the generation fuel cost and the obtained results were compared with other nature-inspired algorithms, such as PSO and ACO. According to [18], the ABC showed better results in minimizing the generation fuel cost than the other algorithms. In [19] and [20] a PSO algorithm has been proposed to minimize the generation fuel cost. However, a comparison with other optimization algorithms is not included in these papers. In [21], the Newton Raphson method has

been used to initialize the population of the PSO algorithm. The proposed PSO algorithm has been used to minimize the generation fuel cost. The GWO and differential evolution (DE) algorithms [22] have been employed to minimize the generation fuel cost and active and reactive power losses. In other studies, several OPF objectives have been considered. The generation fuel cost and active power loss have been reduced by using the HHO algorithm [23], salp swarm algorithm (SSA) [24] and moth-flame optimization (MFO) [25]. In [26-28], the PSO, biogeography-based optimisation (BBO) and GSA were employed to solve OPF problems including fuel cost minimization, voltage profile improvement, and voltage stability enhancement. In [29-31] the sparrow search algorithm (SSA) and monarch butterfly optimization (MBO), grasshopper optimization algorithm (GOA), multi-verse optimizer (MVO) and HHO have been employed to reduce the generation fuel cost, active power transmission loss and improve the voltage profile by minimizing the voltage deviation. In [32] and [33-35] the generation fuel cost, active power loss, voltage deviation have been minimized and the voltage stability has been improved by using the FA, dragonfly algorithm (DA), moth swarm algorithm (MSA), ABC, DSA and efficient sine cosine optimization algorithm (ESCA). In [36], the whale optimization algorithm (WOA) has been applied to solve the OPF problem. The objective functions that have been considered include fuel cost reduction and active and reactive power loss minimization. In [37] an enhanced GA has been proposed to solve the OPF. Three objectives have been considered namely, minimizing the generation fuel cost, active power loss and enhancing the voltage stability of the power system. In [38], the SCA and modified SCA (MSCA) have been proposed to minimize the generation fuel cost, and active and reactive power loss and improve the voltage profile. In [35] an efficient sine cosine optimization algorithm (ESCA) has been proposed. In [39, 40, 41], five objectives namely, reduction of generation fuel cost, voltage deviation, active and reactive power losses and improvement of voltage stability have been optimized by using the black-hole optimization (BHBO) and GWO algorithm. Some of the studies hybridized different algorithms to solve the OPF problem, such as [42-44]. However, the OPF is highly non-linear, non-convex and complex optimization problem, thus this hybridization will lead to an increase in the complexity of the optimization process. Table 1. presents a summary of the nature-inspired algorithms that have been applied to solve the OPF problem with different objective functions.

Although the effectiveness of nature-inspired algorithms for solving optimization problems has been proven in different fields, the algorithm that obtained the best result in solving an optimization problem may not be able to achieve the same result in solving other optimization problems. This is due to the search behaviour used in the algorithm represented by the exploration and exploitation processes and the characteristics of an optimization problem. Therefore, the performance of an algorithm depends on the optimization problem under consideration. This encourages researchers to propose more nature-inspired optimization algorithms to solve the OPF problems.

One of the recently proposed nature-inspired metaheuristics is the honey badger algorithm (HBA) algorithm, which is based on the foraging behaviour of honey badger in nature [45]. Its advantage includes performing a dynamic search behaviour to find the food source, which helps in maintaining the trade-off balance between exploration and exploitation. Another advantage of HBA, it has a few parameters to adjust compared to other recently proposed algorithms, such as the African vultures optimization algorithm (AVOA) [46], HGSO [11], cicada swarm optimization [47] and Coronavirus herd immunity optimizer (CHIO) [48]. Furthermore, a sensitivity analysis for the control parameters is not available for these algorithms. In general, the values of control parameters have a significant impact on the performance of an optimization algorithm. In [45], the HBA has been tested using benchmark functions with diverse properties and real-world engineering problems. According to [45], the HBA is superior to other metaheuristics proposed in the literature, among them, PSO [49], MFO [50], WOA [51], GOA [52] and HHO [10]. In solving real-world problems [45], the HBA has shown superior performance compared to the recently proposed metaheuristics [11, 46, 47]. However, the convergence analysis presented in [45] showed that the HBA has a drawback of trapping in local optima especially in solving a complex optimization problem. Therefore, to enhance the ability of HBA to escape from local optima, this paper proposes a modified honey badger algorithm (MHBA) which integrated with opposition-based learning strategy (OBL) [53] to maintain the population diversity and produce feasible solutions during the search process.

The proposed MHBA is validated with the OPF problem under different objective functions, namely generation fuel cost minimization, active power and reactive power transmission losses minimization, voltage deviation and voltage stability enhancement. Furthermore, both equality and inequality constraints

in the electric power system have been considered, and the results obtained demonstrate that the proposed method provides effective and remarkable results for solving the OPF problem.

The main contributions of this paper are as follows:

- Solving the OPF problem using MHBA with different objective functions.
- Mitigating the drawbacks of the original HBA by improving the search process.
- Testing the effectiveness of the proposed MHBA algorithm on the IEEE 30-bus system for different single objective functions with respect to the equality and inequality constraints of the network.
- Comparing the results with other nature-inspired optimization metaheuristics.

The organization of the paper is as follows: section 2 and section 3 describe the mathematical model of the OPF problem and the HBA algorithm, respectively. The proposed MHBA is described in section 4. section 5 presents the application of MHBA to the OPF problem. This is followed by a discussion on the simulation results in section 6. Finally, the conclusion is in section 7.

2. Formulation of the optimal power flow problem

The OPF problem is formulated through a mathematical model composed of objective functions related to a set of various equality and inequality constraints of the electrical network. The goal is to optimize a set of decision variables to satisfy different technical, economic, operational, and environmental objectives, such as the generation fuel cost, and power losses associated with energy transport. In general, an optimization problem can be represented as shown in Eq. (1).

$$\begin{aligned} & \text{Minimize } f(x, s) \\ & \text{subject to } \begin{cases} eq(x, s) = 0 \\ ieq(x, s) \leq 0 \end{cases} \end{aligned} \quad (1)$$

where $f(x, s)$ is the objective function, $eq(x, s)$ is the set of equality constraints, $ieq(x, s)$ is the set of inequality constraints, x and s are the set of control (independent) and state (dependent) variables, respectively.

2.1 Decision variables

In the OPF problem, the decision variables are classified into control and state variables. The control variables are 24 variables, including active

power of generators excluding the generator at the slack bus, the generator bus voltages, reactive power generation of shunt capacitors, and tap position of transformers [54]. The control variables are 24, that is, the active power output of five generators (except the balance node), six generation bus voltages, four transformer tap positions, and nine injected reactive power of shunt compensator [54]. The set of control variables formulations can be represented as $x = [P_{G,2} \dots P_{G,NG}, V_{G,1} \dots V_{G,NG}, Q_1 \dots Q_{C,NC}, T_1 \dots T_{NT}]$, where P_G is the active power generation at the generator buses (PV) except at the slack bus and NG is the number of generators. V_G represents the generator voltage and T is the tap-settings of transformers, where NT is the number of tap transformers. QC is the shunt VAR compensation, where NC is the number of compensator units [39]. The state variables are calculated from the control variables. These variables can be represented as a vector $u = [P_{G,1}, V_{L,1} \dots V_{L,NL}, Q_{G,1} \dots Q_{G,NG}, S_{1,1} \dots S_{1,nl}]$, where NL , and nl are the number of load buses (PQ), and the number of transmission lines, respectively. S_l is the transmission line flow. The state of the electrical power system is completely determined by the values of these variables [39].

2.2 Objective function

The OPF problem includes several objective functions described as follows.

2.2.1. Minimizing the generation fuel cost (FC)

This objective function includes minimizing the total fuel cost of generation. The mathematical model is formulated as in Eq. (2) [39].

$$f_{cost}(X) = \sum_{i=1}^{NG} (a_i + b_i P_{G,i} + P_{G,i}^2) \quad (2)$$

where $f_{cost}(X)$ is the total fuel cost function (\$/hr), a_i , b_i , c_i is the cost coefficients of generator i and NG is the number of generators.

2.2.2. Minimizing the active power transmission loss (APL)

In a power system, the total power generated by all generators is supplied to loads through transmission lines. The transmission of energy cause energy loss thus minimizing the active power loss in

the transmission lines is considered an important objective which can be expressed as shown in Eq. (3) [39].

$$P_{loss} = \sum_{i=1}^{NB} P_{G,i} - \sum_{i=1}^{NB} P_{D,i} \quad (3)$$

where P_D is real load demand and NB denotes the total number of buses.

2.2.3. Minimization of reactive power transmission loss (RPL)

The voltage stability margin of a power system depends on the availability of reactive power to support the transportation of real power from sources to sinks. This can be achieved by minimizing the total VAR loss as shown in Eq. (4) [39].

$$Q_{loss} = \sum_{i=1}^{NB} Q_{G,i} - \sum_{i=1}^{NB} Q_{D,i} \quad (4)$$

2.2.4. Improving the voltage profile

In general, the voltages are bounded between upper and lower limits within the inequality constraints. The goal is to determine the control variables that improve the voltage profile by minimizing the VD at the PQ buses. Thus, this objective function can formulate as shown in Eq. (5) [39].

$$VD = \sum_{i=1}^{NL} |(V_i - 1.0)| \quad (5)$$

2.2.5. Voltage stability enhancement

Voltage stability is provided if a system can constantly maintain an acceptable voltage, at all system buses, under normal operating conditions, after an increase in load, after a configuration change, or when the power system is subject to voltage collapse. The system stability index (L) is employed to detect voltage instability [55]. Hence, the voltage stability of the power system can be enhanced by minimizing the L values at every bus of the system and consequently the global power system L_{max} . This value varies between 0 (no-load case) to 1 maximum loading point (voltage collapse case), Thus, the objective function can be formulated as shown in Eq. (6) [39].

$$L_{max} = \max(L_i) \quad i = 1, 2, \dots, NL \quad (6)$$

2.3 Constraints

The parameters of a power system must meet certain constraints to operate in a safe and stable environment. These constraints include inequality and equality constraints.

2.3.1 Equality constraint

The equality constraint is given by the load balance equations, that is, those obtained by imposing active and reactive power balance constraints on all nodes of the system. These equality constraints are formulated as shown in Eqs. (7, 8), respectively [39].

Real power constraints

$$P_{G,i} - P_{D,i} - V_j \sum_{j=i}^{NB} [G_{ij} \cos(\theta_{ij}) + B_{ij} \sin(\theta_{ij})] = 0 \quad (7)$$

Reactive power constraints

$$Q_{G,i} - Q_{D,i} - V_i \sum_{j=i}^{NB} V_j [G_{ij} \sin(\theta_{ij}) - B_{ij} \cos(\theta_{ij})] = 0 \quad (8)$$

where G_{ij} and B_{ij} are the conductance and susceptance, respectively, between bus i and bus j . $\theta_{ij} = \theta_i - \theta_j$ is the phase angle between θ_i and θ_j .

2.3.2. Inequality constraint

The inequality constraints reflect the operating limits imposed on the devices and the power electrical system. These constraints include generator voltage limits, active power generated at the slack bus, generated reactive power, transformer constraints, shunt VAR compensator constraints and load bus voltage as shown in Eqs. (9-14), respectively [39].

Generator voltage limits

$$V_{G,i}^{min} \leq V_{G,i} \leq V_{G,i}^{max} \quad i = 1, \dots, NG \quad (9)$$

Active power generated at slack bus

$$P_{G,i}^{min} \leq P_{G,i} \leq P_{G,i}^{max} \quad i = 1, \dots, NG \quad (10)$$

Generated reactive power

$$Q_{G,i}^{min} \leq Q_{G,i} \leq Q_{G,i}^{max} \quad i = 1, \dots, NG \quad (11)$$

Transformer constraints

$$T_i^{min} \leq T_i \leq T_i^{max} \quad i = 1, \dots, NT \quad (12)$$

Shunt VAR compensator constraints

$$Q_{G,i}^{min} \leq Q_{GC,i} \leq Q_{G,i}^{max} \quad i = 1, \dots, NC \quad (13)$$

Load bus voltage

$$V_{L,i}^{min} \leq V_{L,i} \leq V_{L,i}^{max} \quad i = 1, \dots, NC \quad (14)$$

3. The honey badger algorithm

This section presents the mathematical model of the HBA. Like any other population-based metaheuristic, the HBA algorithm starts with the initialization of candidate solutions which are randomly distributed in the search space. The position of each candidate solution is represented as a vector, $X_i = (x_1, x_2, \dots, x_D)$ in D dimension. Each solution is calculated as shown in Eq. 15.

$$X_i = LB + r_1 \times (UB - LB); \quad i = 1, 2, \dots, N \quad (15)$$

where N is the number of the solutions in the search space (population size). LB and UB are the lower and upper boundaries, respectively, of the search space. r_1 is a random number in interval $[0, 1]$. The main search process of the HBA is divided into two phases, namely the digging (exploration) and honey (exploitation) phases. These processes are performed to update the position of the honey badger and generate new solutions.

3.1 Digging phase

The digging phase is simulated based on the Cardioid motion and formulated in Eq. (16).

$$X_{new} = X_{prey} + F \times \beta \times I \times X_{prey} + F \times r_2 \times \alpha \times d_i \times |\cos(2\pi r_3) \times [1 - \cos(2\pi r_4)]|; \quad i = 1, 2, \dots, N \quad (16)$$

where r_2 , r_3 , and r_4 are three different random numbers in the interval $[0,1]$. X_{prey} represents the location of the prey in the search space which is the best solution found so far. $\beta \geq 1$ represents the ability of the honey badger to get food. In the digging phase, a honey badger heavily relies on smell intensity, I , of prey, the distance between the prey, X_{prey} , and honey badger, $d_i = X_{prey} - X_i$, and time-varying search influence factor α . The smell intensity is determined according to the concentration strength of the prey (location of prey), S , and distance between the prey and i th honey badger. The motion is proportional to the smell and given by inverse square law [56] as shown in Fig. 1 and is defined by Eq. (17).

$$I_i = r_5 \times \frac{S}{4\pi d_i^2} \quad ; r_5 \in [0,1] \quad (17)$$

$$S = (X_i - X_{i+1})^2$$

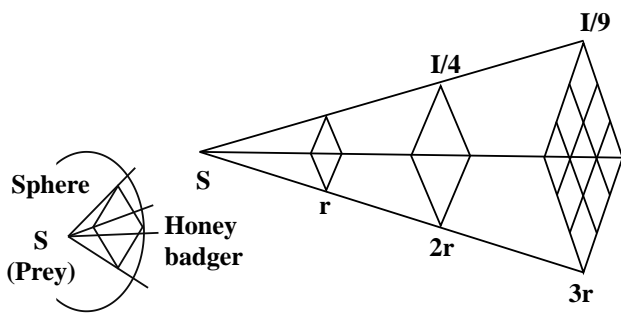


Figure. 1 Inverse-square law [45]

The search direction is changed based on the value of a flag F , to explore the search space rigorously. The flag F is calculated using Eq. (18).

$$F = \begin{cases} 1 & \text{if } r_6 \leq 0.5 \\ -1 & \text{else} \end{cases}; r_6 \in [0,1] \quad (18)$$

The exploration and exploitation are balanced using the density factor (α) that is defined as shown in Eq. (19).

$$\alpha = C \times \exp\left(\frac{-t}{t_{max}}\right) \quad (19)$$

where t is the current iteration number, t_{max} is the maximum number of iterations. C is a constant ≥ 1

3.2. Honey phase

The honey phase simulates the behaviour of a honey badger when it follows the honeyguide bird to reach the beehive, as shown in Eq. (20).

$$X_{new} = X_{pry} + F \times r_7 \times \alpha \times d_i; \quad r_7 \in [0,1] \quad (20)$$

4. Modified honey badger algorithm (MHBA)

Although the HBA algorithm has the advantages of dynamic searchability, it has a drawback of trapping in local optima due to the population diversity loss, especially, in solving a complex optimization problem. In this context, this paper aims to improve the original HBA by maintaining the population diversity during the search process. In the proposed MHBA, the search process has been improved by maintaining the diversity of the population of the badgers. This leads to better convergence toward the global optima. The major change to the original HBA is the OBL strategy is deployed to preserve the diversity of candidate solutions and improve the convergence of the original

HBA. This also ensures efficient searching of the whole search space.

The OBL strategy [53] has been widely used to generate solutions with better diversity. In the OBL strategy, a solution located in the opposite direction, \check{X} , of a candidate solution, X is calculated to explore more promising regions of the search space. The solution \check{X} , is calculated as shown in Equation (21) [53].

$$\check{X} = \vec{lb} + \vec{ub} - \vec{X} \quad (21)$$

where ub and lb are upper and lower bounds, respectively. The OBL strategy has been applied in several studies to initialize a population of solutions [57-61]. In this paper, the OBL strategy has been used to maintain population diversity during the search process. This prevents the MHBA algorithm from trapping in local optima and achieving a feasible solution for the OPF problem. In the proposed MHBA, the new solutions are generated using Eqs. (16,20), as described in section 3. However, at each iteration, the best fitness value, $f_{prey,t}$ of the X_{prey} achieved at the current iteration, t , is compared with $f_{prey,(t-1)}$ value achieved at the previous iteration, $t-1$. If the value of f_{prey} is never changed for k number of iterations (k is set to two in this paper), the OBL strategy will be partially performed on the first n worst solutions (n is set to 10 in this paper). In this way, the feasible solution achieved so far will not be lost and the worst solutions will be replaced with new solutions. This process helps in improving the exploration process and preserves the trade-off balance between exploration and exploitation.

5. Application of MHBA to the OPF problem

This section presents the step-by-step implementation of the MHBA in solving the OPF problem. Various steps involved in solving the optimal power flow problem using the MHBA are presented in the flowchart shown in Fig. 2.

The proposed MHBA algorithm for solving the OPF problem is summarized as follows:

1. Load the power system data.
2. Initialize the N population of solutions $X_i; i = 1, \dots, N$.
3. Evaluate the position X_i , of each honey badger by using an objective function of the OPF problem
4. Save the best solution, X_{prey} and the best fitness value f_{prey} .
5. Update the position of a honey badger, X_{new} using Eqs. (16-20) and calculate their fitness values.

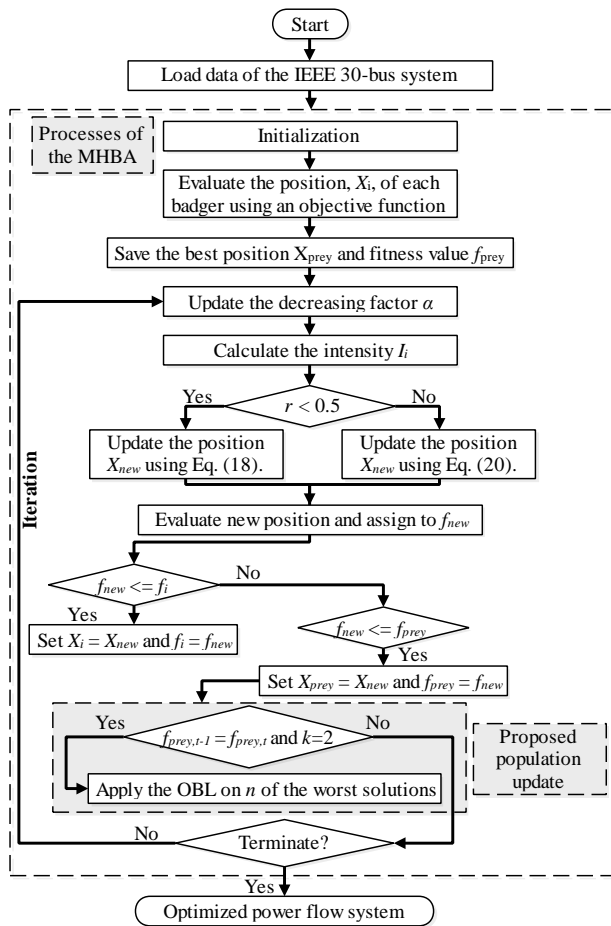


Figure. 2 Processes of HBA in solving the OPF problem on the IEEE 30-bus system

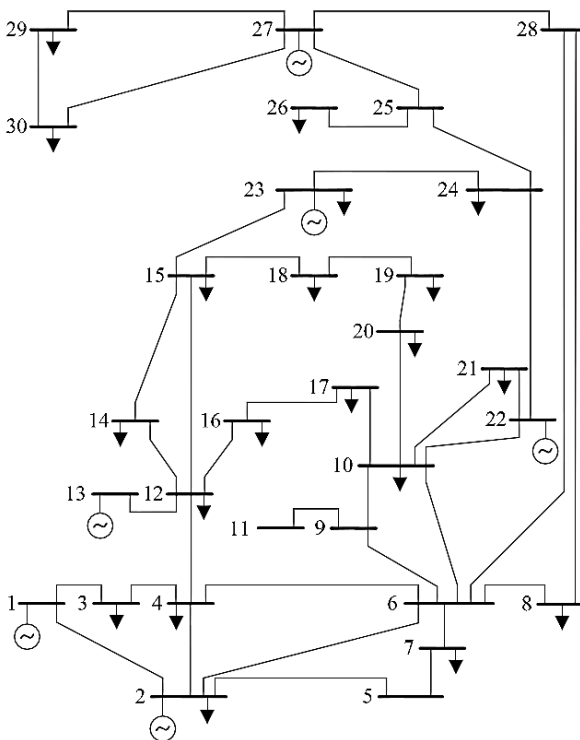


Figure. 3 IEEE 30-bus system [62]

6. Compare $f_{prej,t}$ with $f_{prej,t-1}$. If $f_{prej,t}$ is equal to f_{prej} , and $k = 2$ perform the OBL strategy on the k worst solutions.
7. Replace the worst solutions with the solutions \tilde{X} .
8. If the termination condition is not met, go back to step 5, otherwise, STOP.

6. Results and discussion

The performance of the proposed MHBA has been validated by solving the OPF problem with different objective functions which include, minimization of the generation fuel cost of the power system and minimization of active and reactive transmission line losses, VD and enhancing the voltage stability of the system. The experiments have been carried out on the IEEE 30-bus system. The IEEE 30-bus system consists of six generator buses (buses 1, 2, 5, 8, 11 and 13), 24 load buses, four variable tap transformers (6–9, 6–10, 4–12 and 27–28), 41 transmission lines and two shunt reactors (buses 10 and 24). The information on the 30 IEEE buses system is taken from [39]. Fig. 3 shows the one-line diagram of the IEEE 30-bus system.

The results obtained by the MHBA are compared with the results found by HBA in solving the OPF problem with different objectives functions, namely fuel cost minimization, minimization of active and reactive power transmission line losses, minimization of VD, and enhancement of the voltage stability. Each algorithm is executed 30 times for each objective function. The executions have ended after performing 500 iterations. The parameters of the HBA algorithm are set as recommended by its respective authors [45]. The BHA and MBHA optimization algorithms were compared based on the mean, standard deviation (STD), and best and worst fitness values obtained. Table 2 shows the best results obtained by the HBA and MHBA over 30 runs in optimizing each objective function. Due to the restricted number of pages, the values of control parameters obtained are not included.

In Table 2 the values in bold represent the best fitness values achieved in solving each objective function, namely generation fuel cost (FC), active transmission line loss (APL) and reactive transmission line loss (RPL), VD and Lmax. It is worth mentioning that the negative and positive value of reactive power represents the condition operating of the power system. the generator can inject (positive) or absorb (negative) reactive power [63]. The MHBA shows the global optima value at 799.074 \$/hr for generation fuel cost. For minimizing the APL and RPL, the MHBA has a lower value of

Table 1. The best fitness values for each objective function were achieved by using the MHBA and HBA algorithms over 30 runs.

| Objective | Algorithm | Mean | STD | Best | Worst |
|------------|-----------|----------------|--------|----------------|---------|
| FC (\$/hr) | HBA | 800.187 | 1.420 | 799.181 | 804.727 |
| | MHBA | 799.304 | 0.518 | 799.074 | 802.003 |
| APL (MW) | HBA | 3.1186 | 0.2911 | 2.8685 | 3.8790 |
| | MHBA | 2.9252 | 0.0559 | 2.8659 | 3.0929 |
| RPL (MVAR) | HBA | -22.345 | 2.507 | -20.200 | -11.923 |
| | MHBA | -23.886 | 0.215 | -24.262 | -23.420 |
| VD (pu) | HBA | 0.1096 | 0.016 | 0.0863 | 0.1461 |
| | MHBA | 0.1000 | 0.0078 | 0.0861 | 0.1133 |
| Lmax | HBA | 0.1043 | 0.002 | 0.096 | 0.1086 |
| | MHBA | 0.1031 | 0.0016 | 0.096 | 0.1065 |

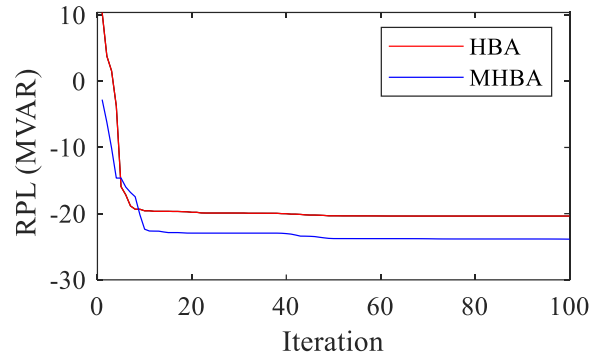


Figure. 6 The convergence of the MBHA and BHA in minimizing the reactive power transmission loss

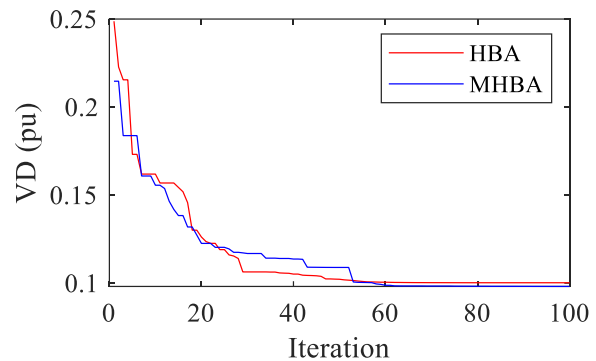


Figure. 7 The convergence of the MBHA and BHA in minimizing the VD

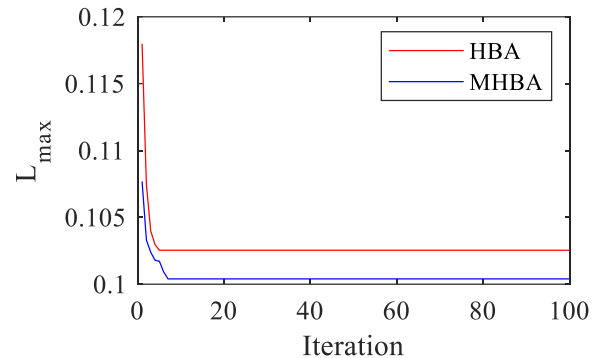


Figure. 8 The convergence of the MBHA and BHA in minimizing the Lmax.

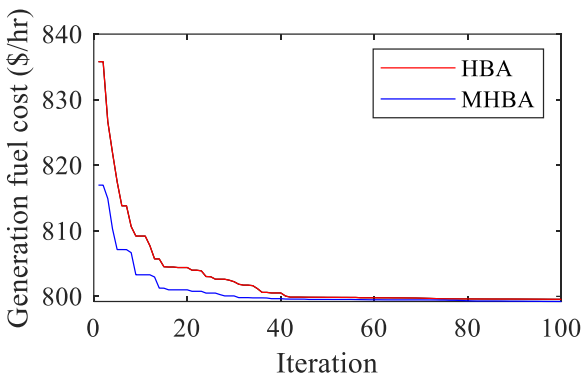


Figure. 4 The convergence of the MBHA and BHA in minimizing the generation fuel cost

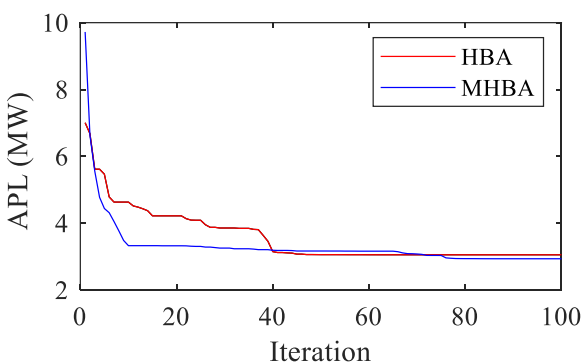


Figure. 5 The convergence of the MBHA and BHA in minimizing the active power transmission loss

2.8659 MW and -24.262 MVAR, respectively. The MHBA achieved a minimum VD value at 0.0861 and similar L_{max} values pu at 0.096. Based on the results,

it is seen that the proposed MHBA provides superior results for solving the OPF problem with different objectives compared to the HBA. The convergences of MHBA and HBA in minimizing the FC, APL, RPL, VD and L_{max} , are illustrated in Figs. 4-8.

It can be observed from Figs. 4-8 that the proposed MHBA algorithm achieved better convergence compared to the HBA. This is due to the infeasible solutions being killed when it is not improved after a certain number of iterations and the OBL strategy prevents the homogeneous state of the population by producing new solutions. To measure the diversity of the population during the

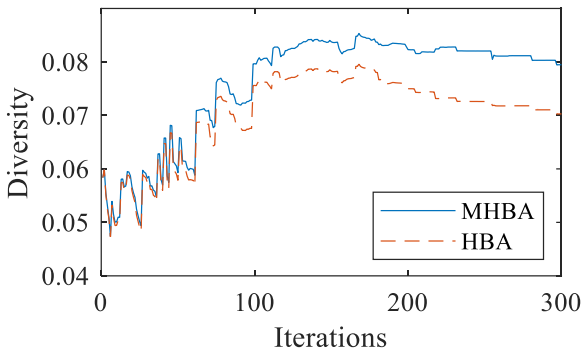


Figure. 9 The diversity of the population with the iteration obtained by the MBHA and BHA in minimizing the FC

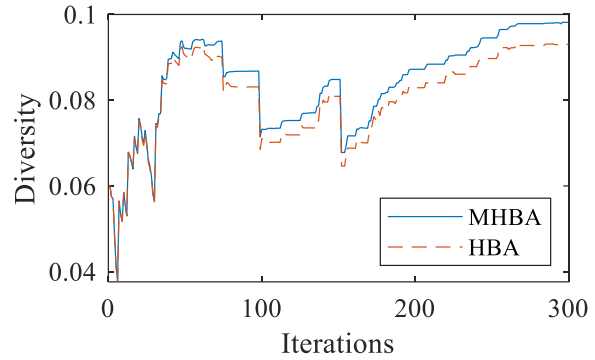


Figure. 12 The diversity of population with the iteration obtained by the MBHA and BHA in minimizing the VD

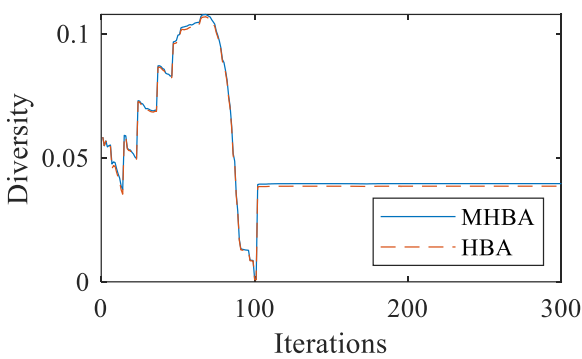


Figure. 10 The diversity of the population with the iteration obtained by the MBHA and BHA in minimizing the APL

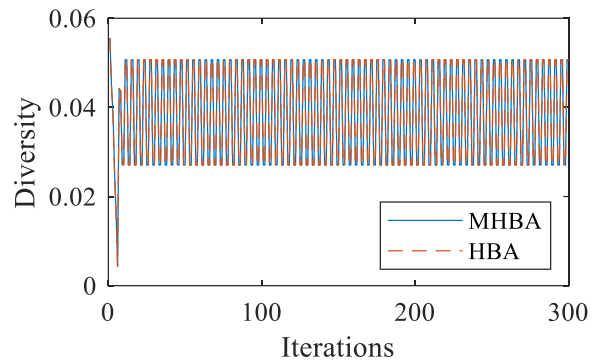


Figure. 13 The diversity of the population with the iteration obtained by the MBHA and BHA in minimizing the L_{max}

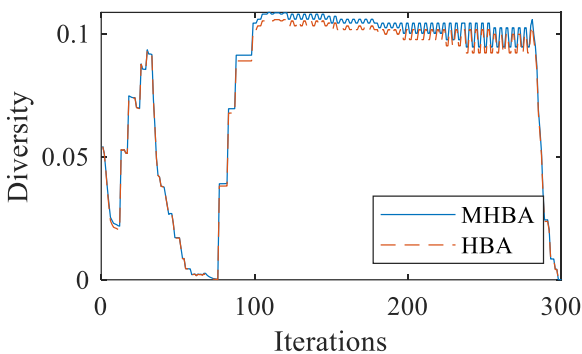


Figure. 11 The diversity of the population with the iteration obtained by the MBHA and BHA in minimizing the RPL

optimization process, the diversity measure [64] has been used. Where the higher value indicated better diversity. Figs. 9-13 show the diversity of the population at each iteration obtained by MHBA and HBA in optimizing each objective function of the OPF problem.

In Figs. 9-13, the connected and disconnected lines represent the diversity of population during the iterations obtained by the MHBA and HBA, respectively in optimizing each objective function.

According to the values of diversity, the MHBA algorithm has achieved higher diversity for the solutions in minimizing the FC, APL, RPL and VD. This is due to the search behaviour of MHBA that maintains the population diversity during the search process. In minimization of the L_{max} value, both MHBA and HBA achieved almost the same diversity for the solutions.

To verify the effectiveness of the MHBA algorithm in solving the OPF problem, it has been compared with other optimization algorithms reported in the literature, namely, PSO [26, 42, 65], GWO [22, 41], ABC [33], SCA [38], HHO [31], EGA [37], SA [66], DE [67], BHBO [47], GSA [28], BHBO [39], DSA [34], BBO [34] algorithms. In this comparison, the five objectives, fuel cost minimization, minimization of active and reactive power transmission line losses, minimization of VD, and enhancement of the voltage stability have been considered. Tables 3-7 show the best results obtained by each algorithm in optimizing each objective function.

In Table 3, the minimum generation fuel cost obtained by the MHBA is (799.073 \$/hr), which is 0.17%, 0.08%, 0.70%, 0.13%, 0.17% lower than PSO

Table 2. Best generation fuel cost obtained by each algorithm

| Algorithm | Generation fuel cost (\$/hr) | | | | |
|-----------|------------------------------|--------|--------|--------|-----------|
| | FC | APL | RPL | VD | L_{max} |
| MHBA | 799.073 | 8.626 | 3.902 | 1.843 | 0.116 |
| PSO [26] | 800.410 | - | - | 0.877 | 0.130 |
| GWO [41] | 799.7005 | 8.787 | -0.735 | 1.36 | 0.129 |
| ABC [33] | 800.660 | 9.0328 | - | 0.9209 | 0.1381 |
| SCA [38] | 800.102 | 9.063 | - | 2.083 | - |
| HHO [31] | 804.141 | 7.97 | - | 0.391 | - |

Table 3. Best active power losses obtained by each algorithm

| Algorithm | Active power transmission loss (MW) | | | | |
|-----------|-------------------------------------|-------------|--------|--------|-----------|
| | FC | APL | RPL | VD | L_{max} |
| MHBA | 967.10 | 2.87 | -18.98 | 2.0486 | 0.1167 |
| PSO [65] | 954.34 | 3.32 | - | - | - |
| ABC [33] | 967.68 | 3.11 | - | 0.90 | 0.14 |
| EGA [37] | 967.86 | 3.20 | - | - | - |
| SCA [38] | 966.79 | 2.94 | - | 1.82 | - |
| HHO [31] | 915.09 | 4.56 | - | - | - |

Table 4. Best reactive power losses obtained by each algorithm

| Algorithm | Reactive power loss minimization (MVAR) | | | | |
|-----------|---|-------|---------------|-------|-----------|
| | FC | APL | RPL | VD | L_{max} |
| MHBA | 967.540 | 3.050 | -24.16 | 1.066 | 0.127 |
| PSO [42] | 966.95 | 2.91 | -23.76 | 0.91 | 0.13 |
| SA [66] | 799.45 | 5.13 | -20.34 | 0.985 | - |
| DE [67] | 799.2891 | 6.44 | -21.56 | 1.85 | - |
| BHBO [39] | 924.14 | 3.75 | -20.15 | 0.49 | 0.14 |
| GWO [41] | 915.64 | 4.029 | -21.16 | 1.846 | 0.12 |

Table 5. Best VD value obtained by each algorithm for improving the voltage profile

| Algorithm | Voltage deviation (pu) | | | | |
|-----------|------------------------|-------|--------|--------------|-----------|
| | FC | APL | RPL | VD | L_{max} |
| MHBA | 889.611 | 9.432 | 10.012 | 0.087 | 0.137 |
| PSO [26] | 806.38 | - | - | 0.089 | 0.14 |
| HHO [31] | 849.806 | 5.79 | - | 0.1494 | - |
| SCA [38] | 843.60 | 8.50 | - | 0.108 | - |
| MSCA [38] | 849.28 | 7.083 | - | 0.103 | - |
| GSA [28] | 804.31 | 0.10 | - | 0.093 | 0.14 |

[26], GWO [41], ABC [33], SCA [38], HHO [31], respectively. Compared to the initial case (901.952 \$/hr) the total fuel cost obtained by HBA is considerably reduced by 11.41%. On the other hand, the worst result was achieved by HHO (804.141\$/hr). The results demonstrate that the proposed algorithm is superior for minimizing the generation fuel cost compared to the other algorithms. This makes the solution obtained by the MHBA more economically than the solutions of other algorithms. The value of other objectives namely, minimization of active

power, reactive power transmission line loss and VD, and enhancing the voltage stability, have been calculated using the best solution obtained by each algorithm in minimizing the generation fuel cost.

Table 4 shows that the MHBA has achieved the minimum total active power transmission loss of (2.87 MW). This value is 13.55%, 7.72%, 10.31%, 2.38%, 37.06% lower than PSO [65], ABC [33], EGA [37], SCA [38] and HHO [31] algorithms, respectively, and 50.71% lower than the initial case (5.8225 MW). The results reveal that the proposed algorithm showed the best results among others in terms of minimization of active power transmission loss. On the other hand, the highest total active power transmission losses value was obtained by HHO [31] (4.56 MW). The value of other objectives namely, minimization of generation fuel cost, reactive power transmission line loss and enhancing the voltage stability and voltage profile, has been calculated using the best solution obtained by each algorithm in minimizing the active power losses.

In Table 5, the minimum reactive power loss value obtained by the MHBA at -24.16 MVAR is considered 80.94% lower than the initial case (-4.606 MVAR). Furthermore, this value is 1.66%, 15.81%, 10.76%, 16.60%, 12.42% lower than PSO [42], SA [66], DE [67], BHBO [47] and GWO [41] algorithms, respectively. On the other hand, the BHBO [39] showed the highest value at (-20.1522 MVAR). The fitness value of other objectives namely, minimization of generation fuel cost, active power transmission line loss and enhancing the voltage stability and voltage profile, has been calculated using the best solution obtained by each algorithm in minimizing the reactive power losses.

Table 6 shows that the MHBA achieved the minimum VD value of 0.087 pu, which is 2.25%, 41.61%, 19.44%, 15.53%, 6.45% lower than PSO [26], HHO [31], SCA [38], MSCA [38], GSA [28] optimization algorithms. This indicates that the HBA has a better voltage profile compared to the solutions obtained by other algorithms. Furthermore, the VD value of HBA is 92.43% lower than the initial case (1.1496 pu). The HHO has the worst VD value of (0.1494 pu). This value is slightly lower than the initial case which indicates that the solution of the HHA algorithm did not improve the voltage profile of the power system. The fitness value of other objectives has been calculated using the best solution obtained by each algorithm in minimizing the VD.

In Table 7, the MHBA algorithms achieved the best result in minimizing the L_{max} value of (0.096). This value is 44.28 lower than the initial case (0.1723) and 23.20%, 18.64%, 17.95%, 22.58%, 2.04% lower than the PSO [26], GWO [41], BHBO

Table 6. Best L_{\max} value obtained by each algorithm for stability enhancement

| Algorithm | Voltage stability enhancement | | | | |
|-----------|-------------------------------|-------|--------|---------|--------------|
| | FC | APL | RPL | VD | L_{\max} |
| MHBA | 878.0918 | 7.390 | 16.591 | 3.220 | 0.096 |
| PSO [26] | 801.160 | - | - | 0.961 | 0.125 |
| GWO [41] | 800.664 | 9.214 | 2.132 | 1.8076 | 0.118 |
| BHBO [39] | 805.0087 | 8.426 | 7.239 | 1.59705 | 0.117 |
| DSA [34] | 967.472 | 3.422 | - | - | 0.124 |
| BBO [34] | 917.360 | 4.950 | - | - | 0.098 |

[39], DSA [34], BBO [34] algorithms, respectively. The results indicate that the solutions of the HBA algorithm provide better stability compared to the solution of the other algorithms and the initial case. The worst L_{\max} value of (0.125) was obtained by PSO. The value of other objectives namely, minimization of generation fuel cost, active power, reactive power transmission line loss and enhancing the voltage profile, have been calculated using the best solution obtained by each algorithm in minimizing the L_{\max} .

The results showed that the MHBA has a great ability in jumping out of local optima, which indicates the ability of the algorithm to explore the search space and to generate solutions with better diversity and convergence compared to the original HBA and other algorithms.

7. Conclusion

In this article, the MHBA algorithm has been proposed to improve the searchability of the original HBA for solving the OPF problem. The OBL strategy that has been used in the proposed MHBA, can strengthen the diversity of the population, and avoid getting stuck into a local optimum during the optimization process. The OPF problem is a highly non-linear, non-convex and complex optimization problem with several decision variables and equality and inequality constraints. Different objective functions were considered, namely minimization of generation fuel cost, minimization of active and reactive power transmission line losses, minimization of VD, and enhancing the voltage stability. The proposed MHBA algorithm has been tested on the IEEE 30-bus test system and evaluated based on the best solution obtained. Furthermore, the results for various objective functions of the OPF problem were compared with the original HBA and other optimization algorithms reported in the literature. The results demonstrated the superiority of the proposed algorithm in solving the OPF problem. The MHBA achieved promising results in optimizing each objective. This is due to the dynamic search strategy and effective search behaviour used in the

algorithm represented by the proposed population update that maintains the population diversity and helps the algorithm to escape out of local optima. For future work, it is possible to test other recently proposed algorithms in solving the OPF problem. Furthermore, in real-world applications, usually, optimization problems tend to integrate several criteria, where two or more different objectives are taken together. Thus, proposing a multi-objective algorithm to solve the multi-objective OPF problem is recommended.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Shaymah Akram Yasear; methodology, Shaymah Akram Yasear; software, Shaymah Akram Yasear; investigation, Shaymah Akram Yasear; resources, Shaymah Akram Yasear; writing—original draft Shaymah Akram Yasear; preparation and visualization, Shaymah Akram Yasear; supervision, Shaymah Akram Yasear; writing—review and editing, Shaymah Akram Yasear and Hayder M. A. Ghanimi.

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