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HUMAN BEHAVIOR BASED OPTIMIZATION ALGORITHM FOR OPTIMAL POWER FLOW PROBLEM WITH DISCRETE AND CONTINUOUS CONTROL VARIABLES

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ABSTRACT
In this work, the most challenging problem of the modern power system named optimal power flow (OPF) is optimized using the novel meta-heuristic optimisation algorithm Human Behavior- Based Optimization (HBBO). HBBO is inspired by human behavior in different field. HBBO has a fast convergence rate due to a use of roulette wheel selection method. So as to resolve the optimal power flow problem, the IEEE-30 busstandard system is used. HBBO is implemented for the solution of suggested problem. The problems considered in the OPF problem are Fuel Cost Reduction, Active Power Losses Minimization, Reactive Power Losses Minimization, Voltage Profile Improvement and Voltage Stability Enhancement. The outcomesachieved by HBBO is compared with Flower Pollination Algorithm (FPA), Particle Swarm Optimization (PSO) and other well-known techniques. Results show that HBBO gives better optimisation values as compared with FPA and PSO that confirms the success of the suggested algorithm.

Keywords:
Optimal power flow, Active Power Losses, Reactive Power Losses, Voltage Stability, Human Behavior-Based Optimization.

INTRODUCTION

At the present time, The OPF (Optimal Power Flow) is a very significant problem and most focused objective for power system scheduling as well as operation [1]. The OPF is the elementary tool which permits the utilities to identify the economic operational and many secure states in the system [2]. The OPF is one of the utmost operating desires of the electrical power network. The prior aim of the OPF is to evaluate an optimum operational state of an electric network by minimizing a specific objective function within the limits of the operational constraints like equality and inequality constraints [3]. Hence, problem of the optimal power flow can be defined as a highly non-linear and non-convex multimodal optimisation problem [4]. From the past few years too many optimisation techniques were used to solve the Optimal Power Flow (OPF) problem [5]. Some conventional methods are utilized to elucidate the proposed problem have been suffered from some limitations like converging at local optima, not suitable for binary or integer problems and also have the assumptions like the convexity, differentiability, and continuity [6]. Hence, these techniques are not suitable for the actual OPF situation [7]. All these limitations are overcome by meta-heuristic optimisation methods like BHBO, TLBO, LCA, etc.

In the present work, a newly introduced meta-heuristic optimisation approach named Human Behavior- Based Optimization (HBBO) is utilized to resolve the problem of Optimal Power Flow. The HBBO technique is a sociological inspired algorithm based on the behavior of the human beings in various fields [8]. The capabilities of HBBO are finding the global solution, fast convergence rate due to a use of roulette wheel selection, can evaluate continuous and discrete optimisation problems. In the present work, the HBBO is applied for the IEEE-30 bus system [9, 10] to resolve the OPF problem. There are five objective cases considered in this paper that have to be optimize using Human Behavior- Based Optimization (HBBO) technique are Fuel Cost Reduction, Active Power Losses Minimization, Reactive Power Losses Minimization, Voltage Profile Improvement and Voltage Stability Enhancement. The result shows the optimal adjustments of control variables in accordance with their limits. The results obtained using HBBO technique has been compared with Flower Pollination Algorithm (FPA), Particle Swarm Optimisation (PSO) and other famous meta-heuristic techniques. The results show that HBBO gives better optimisation values as compared to different methods which prove the strength of the suggested method.

Optimal Power Flow Problem Formulation

As specified before, OPF is a common power flow problem that provides the optimum values of control variables by minimizing a predefined objective function regarding the operating bounds of the system. The OPF may be calculated as [3]:

$$\textbf{\textit{Minimize}}[f(a,b)] \quad (1)$$

$$\textbf{subject to } s(a,b)=0 \quad (2)$$

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And $h(a,b) \le 0$ (3)

Where, b=vector of control variables, a=vector of state variables, *f* (a, b) = objective function, *s* (a, b) = set of equality constraints, *h* (a, b) =set of inequality constraints.

A. Variables

1. Control variables

These variables are adjusted to fulfill the power flow equations. These variables may be represented as [3]:

$$b^T = [P_{G_2} \dots P_{G_{NGen}}, V_{G_1} \dots V_{G_{NGen}}, Q_{C_1} \dots Q_{C_{NCom}}, T_1 \dots T_{NTr}] \quad (4)$$

Where: P_G= real power output at the generator buses not including the slack bus.V_G=Voltage magnitude at generator buses.Q_C=Shunt VAR compensation.T= tap settings of the transformer. NGen, NTr, NCom= no. of generator units, the no. of transformers and the no. of shunt reactive power compensators, respectively.

2. State variables

These variables aredesired to characterize the operating state of the network. These variables can be represented as [3]:

$$a^T = [P_{G_1}, V_{L_1} \dots V_{L_{NLB}}, Q_{G_1} \dots Q_{G_{NGen}}, S_{l_1} \dots S_{l_{Nline}}] \quad (5)$$

Where: P_G= the real power output at reference bus. V_L= the voltage at load buses; Q_G= =the output of reactive power of all generating unit. S_l= the line flows. NLB, Nline= no. of PQ buses, and the no. of lines, respectively.

B. Constraints

Power system constraints may be categorized by equality constraints and inequality constraints.

1. Equality constraints

It reveal the physical behavior of the network. These constraints are [3]:

1.1 Active power constraints

$$P_{Gi} - P_{Di} - V_i \sum_{J=i}^{NB} V_j [G_{ij} Cos(\delta_{ij}) + B_{ij} Sin(\delta_{ij})] = 0 \quad (6)$$

1.2 Reactive power constraints

$$Q_{Gi} - Q_{Di} - V_i \sum_{J=i}^{NB} V_j [G_{ij} Cos(\delta_{ij}) + B_{ij} Sin(\delta_{ij})] = 0 \quad (7)$$

Where, $\delta_{ij} = \delta_i - \delta_j$

Where, NB= No. of buses, P_G= the output of real power, Q_G= the output of reactive power, P_D= real power load demand, Q_D= reactive power load demand, $G_{ij}$and B_{ij}= components of the admittance matrix $Y_{ij} = (G_{ij} + jB_{ij})$ showing the conductance and susceptance among bus i and j, respectively.

2. Inequality constraints

These show the bounds on electrical equipment existing in the network plus the bounds formed to surety system safety [3].

2.1 Generator constraints

For every generator together with the reference bus: voltage, real and reactive outputs should be constrained by the minimum and maximum bounds as follows:

$$V_{G_i}^{lower} \le V_{G_i} \le V_{G_i}^{upper}, \; i = 1, \dots, NGen \quad (8)$$

$$P_{G_i}^{lower} \le P_{G_i} \le P_{G_i}^{upper}, \; i = 1, \dots, NGen \quad (9)$$

$$Q_{G_i}^{lower} \le Q_{G_i} \le Q_{G_i}^{upper}, \; i = 1, \dots, NGen \quad (10)$$

2.2 Transformer constraints

Tap positions of transformer should be constrained inside their stated lower and upper bounds as given below:

$$T_{G_i}^{lower} \le T_{G_i} \le T_{G_i}^{upper}, \; i = 1, \dots, NTr \quad (11)$$

2.3 Shunt VAR compensator constraints

Shunt reactive compensation devices need to be constrained withinlower and upper bounds as given below:

$$Q_{C_i}^{lower} \le Q_{GC_i} \le Q_{C_i}^{upper}, \; i = 1, \dots, NGen \quad (12)$$

2.4 Security constraints

These comprise the bounds of a voltage at PQ buses and line flows. All PQ buses Voltage should not violate from its minimum and maximum operational bounds. Line loading over each line should not exceed to its maximum bounds. These limitations can be expressed as:

$$V_{L_i}^{lower} \le V_{L_i} \le V_{L_i}^{upper}, \; i = 1, ..., NLB \quad (13)$$

$$S_{l_i} \le S_{l_i}^{upper}, \; i = 1, ..., Nline \quad (14)$$

The inequality constraints comprise load bus voltage, the output of real power at reference bus, the output of reactive power and line flow may be encompassed as quadratic penalty functions.

Penalty function can be formulated as [3]: $J_{aug} = J + \partial_P \left(P_{G_1} - P_{G_1}^{lim} \right)^2 + \partial_V \sum_{i=1}^{NLB} (V_{L_i} - V_{L_i}^{lim})^2 + \partial_Q \sum_{i=1}^{NGen} + \partial_S \sum_{i=0}^{Nline} (S_{l_i} - S_{l_i}^{max})^2$

(15)

Where, $\partial_P, \partial_V, \partial_Q, \partial_S =$ penalty factors

U_{lim}= Boundary value of the state variable U.

If U is greater than the maximum bound, U_{lim}takings the value of that one, if U is lesser than the minimum bound U_{lim}takings the value of that bound so:

$$U^{lim} = \begin{cases} U^{upper} & ; U > U^{upper} \\ U^{lower} & ; U < U^{lower} \end{cases} \quad (16)$$

HBBO TECHNIQUE

In social culture, everybody is trying to reach his subjective commitments. A person who may achieves all the goals called successful person. To complete his particular goal, person has to fully dedicate himself to that work. However, the point of views are different from person to person, each individual decides getting some definite goals to get success. To achieve this, individuals are functioning and learning in various arenas and try to expert in it. Amongst all individuals, who are working in a particular arena, one person is highly skilled than the others, so the others aim to study from this expert persons and develop their abilities in that field. According to these human behavior, this algorithm involves the 5stages as follows [8]:

Step 1: Initialization
Step 2: Education
Step 3: Consultation
Step 4: Field change probability
Step 5: Finalization

Step 1. Initialization

This phase dedicated to creating and assessing the primary individuals and distributed in the different area. An individual for Nvar variables is given as follows [8]:

$$\textbf{Individual} = [x_1, x_2, ..., x_{N_{var}}] \quad (17)$$

The algorithm produces N_{pop} of primary individuals and arbitrarily distribute into N_{field} of primary areas. These people develop the culture. The no. of primary individuals in particulararea is given as:

$$\mathbf{N.Ind_i = round\left\{\frac{N_{pop}}{N_{field}}\right\}} \quad (18)$$

Where $N.Ind_i$ is the no. of initial individuals in i[th] field. The function values will be computed after producing the initial individuals. It is defined as follows: $\mathbf{function\ value = f(x_1, x_2, ..., x_{N_{var}})}$

(19)

Step 2. Education

In education phase, each individual efforts to study and enhance themselves by moving around the skilled individual of the particulararea which is known as expert person. It has the greatest function number in particulararea. To model this process, coordinate system is executed and the expert individual is the source. This effortall over the expert individual for a 3-D problem is shown in Fig. 1 and will be executed by varying the coordinates of the individuals in spherical coordinate system. The effort area is restricted by a sphere surrounding the expert individual. The algorithm will catch a random radial coordinate (r) between $r_{min} = k_1 d$ and $r_{max} = k_2 d$, where d is the Euclidian space between the source and individual, and k_i is the weighting factor [8]. Furthermore, the procedure may discover N-1 arbitrary angular coordinates ($\theta_1, \theta_2, ..., \theta_{N-1}$), where θ_{N-1} may be initiatewithin 0 and 2π radians and the another angles chosenwithin 0 and π radians [8].

Step 3. Consultation

In this phase, each individual except the expert selects anarbitrary guide from the culture and consulting with them. In this procedure, the guide may update few of the specific variables. If the updated variables has a superior function cost, then it will be exchanged with it. The no. of random variables that will be updated is achieved by as follows [8]:

$$N_c = \text{round}\{\sigma \times N_{var}\} \tag{20}$$

Where σ is the consultation factor to finds the no. of updated random variables

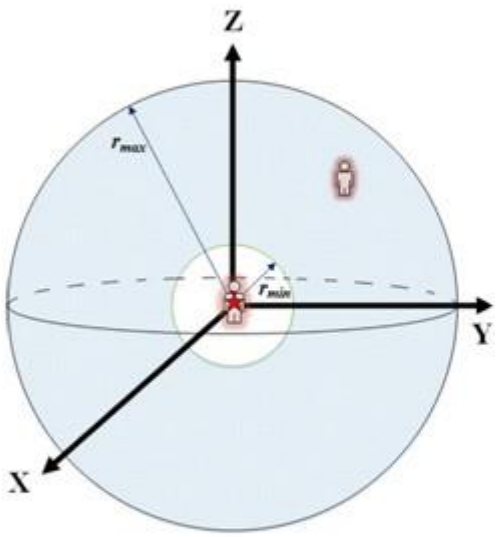

Fig. 1.Education: Moving Around the Expert Individual.

Step 4. Field change probability

In every iteration, a personcanmodify his area. The possibility of shifting the area is evaluated by a rank probability scheme. In this scheme, each area is arranged with respect to itsbest function value, as given below [8]:

$$\text{sort fields} = [\text{field}_1, \text{field}_2, \ldots\ldots, \text{field}_n] \tag{21}$$

Where the best individual of field_1 and field_n has the poorest and the finest function cost from the others, respectively. The updating possibility for every area can be computed as given below:

$$P_i = \frac{O_i}{N_{field} + 1} \tag{22}$$

Where P_i and O_i are the area updating possibility and the sortingcommand for the i_{th} area, respectively. The field having finest function cost is fewerpossible and area having poorest function cost is morepossible for area changing. Through creating anarbitrary number within 0 and 1, the given equation is verified, and if it is satisfied, the field changing occurs [8]:

$$\text{if rand} \leq P_i \rightarrow \text{field changing occurs} \tag{23}$$

Anassortment possibility for every individual will be given as [8]:

$$P.S_j = \left| \frac{f(\text{Individual}_j)}{\sum_{k=1}^{N_{ind}} f(\text{Individual}_k)} \right| \tag{24}$$

Where P.Sj is the selection possibility for the j_{th} individual and N_{ind} is the no. of individuals in the particular field. An individual will be selected using the roulette wheel selection mechanism.

Step 5. Finalization

By executing consultation and education phase, the location of the individuals updated. Hence, function costs of the individuals may be evaluated and algorithm will be ended if the stopping conditions is come; else, the algorithm will jump to phase 2. The terminating conditions are as given below [8]:

a. The no. of iterations equals to maximum iterations.
b. The maximum no. of function calculations is attained.
c. The typical variation in the main function cost is lower than function accepted limit.

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The Control Parameters used in HBBO technique are shown in Table 1.

***Table 1. Control Parameters used in HBBO Technique*.**

Figure 1. **HBBO**	**FPA**	Figure 2. **PSO**
Figure 3. Population Size (Npop)=60	Switch Probability p= 0.8	Figure 4. Cognitive Constant (C1)=2
Figure 5. Random number (r)=0.1	Scaling factor γ= 0.1	Figure 6. Social Constant (C2)=2
Figure 7. Number of fields (Nfield)=20	Scaling factor λ= 1.5	Figure 8. Interia Weight (w)=0.54
Figure 9. K1=0.3, K2=3, Sigma = 0.15	Random number = [0,1]	Figure 10. Random number = [0,1]

APPLICATION & RESULTS

The HBBO technique is implemented to resolve the OPF problem for standard IEEE 30-bus network and for a number of problems with dissimilar objective functions. The program is inscribed in MATLAB 2013a and applied on a 2.60 GHz i5 PC having 4 GB RAM. In the present work, the HBBOsearch agents are selected to be 40.

IEEE 30-bus test system

With the purpose of elucidating the strength of the suggested HBBO technique, it is examined for the IEEE 30-bus network. It comprises [9, 10]: 6 generating units at buses 1,2,5,8,11 and 13, four tap changing transformers between buses 6-9, 6-10, 4-12, and 28-27, nine shunt compensators at buses 10,12,15,17,20,21,23,24 and 29.

Table 2. Limits for different control variables

Variables	Min	Max	Variables	Min	Max
P_{G1}	50	200	P_{G8}	10	35
P_{G2}	20	80	P_{G11}	10	30
P_{G5}	15	50	P_{G13}	12	40
T_{nn}	0.9	1.1	Q_c	0	5
V_G	0.95	1.1	-	-	-

Table 2 shows the min-max limits for different control variables. P_G is the power limit for 6 generators, V_G is the voltage limits for 6 generators, T_{nn} is the tap settings limits for 4 transformers, and Q_c is the limits for 9 shunt compensators.

In addition, the line data, bus data, generator data and the upper and lower bounds for the control variables are specified in [5], [10]. Further, fuel cost ($/h), Ploss (MW), Qloss (MVAR), V_d (p.u.) and L_{max} represent the total fuel cost, the active power losses, the reactive power losses, voltage deviations and stability index respectively.

Case 1:Generation Fuel Cost Minimization.

The fuel cost reduction is the fundamental OPF objective. Hence, Y gives the overall fuel cost of each generating unit and it is describing as [5]:

$$Y = \sum_{i=1}^{NGen} f_i (\$/hr) \tag{25}$$

Where,$f_i$is the fuel cost of the i^{th} generator.

f_i, may be formulated as:

$$f_i = u_i + v_i P_{Gi} + w_i P_{Gi}^2 (\$/hr) \tag{26}$$

Where, u_i, v_i and w_i are the cost coefficients of the i^{th}generator. The coefficients values are specified in [10].

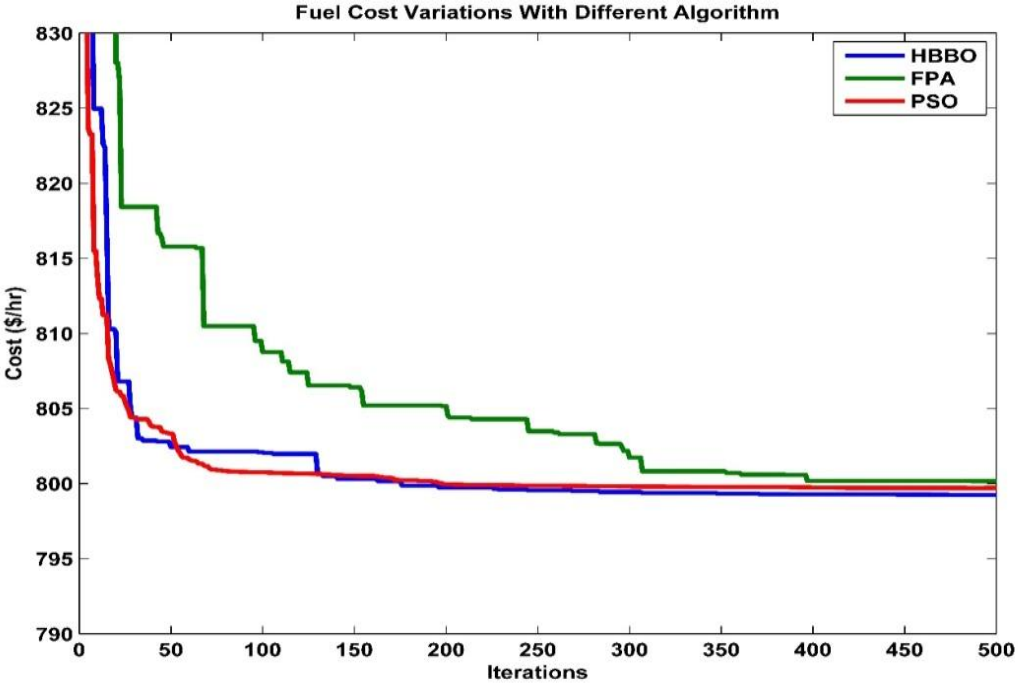

Fig. 2. Fuel Cost Variations with Different Algorithms

Table 3. Optimal Values of Fuel Costs for Different Methods.

Method	Fuel Cost ($/hr)	Method description
HBBO	**799.364**	Human Behavior-Based Optimization
FPA	800.161	Flower Pollination Algorithm
PSO	799.704	Particle Swarm Optimizer
BHBO	799.921	Black Hole-Based Optimization [5]

The fuel cost variations with the different algorithm can be shown in fig. 2. The optimal value of a fuel cost obtained with HBBO is compared with FPA and PSO as shown in table 3. Comparison displays that HBBO give better result as compared to FPA and PSO. The optimisation is done by setting the values of control variables in accordance with their limits. The control variables which are to be adjusted are active power and voltage magnitudes at six generating units along with tap settings of four transformers and nine compensation devices.

Case 2: Minimization of Active Power Losses

In the case 2 the Optimal Power Flow objective is to reduce the active power transmission losses, which can be represented by power balance equation as follows [5]:

$$J = \sum_{i=1}^{NGen} P_i = \sum_{i=1}^{NGen} P_{Gi} - \sum_{i=1}^{NGen} P_{Di} \qquad (27)$$

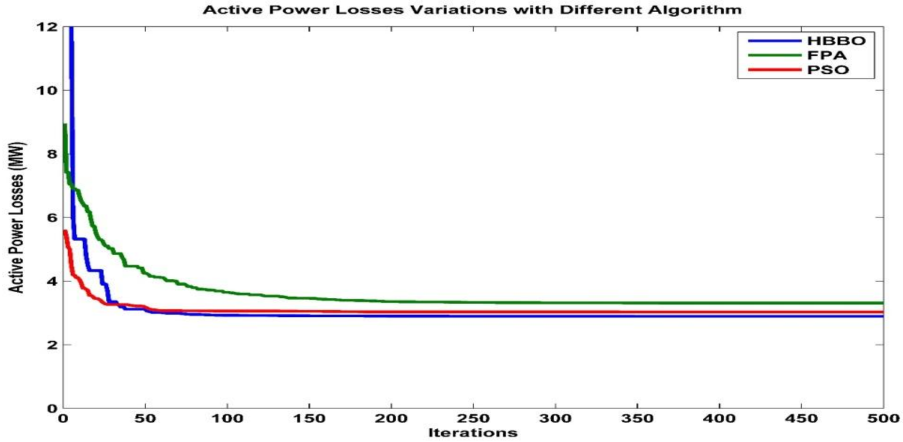

Fig. 3. Active Power Losses Variations with Different Algorithms.

Table 4.Optimal Values of Active Power Losses for Different Methods.

Method	$\mathbf{P_{losses}}$ **(MW)**	**Method description**
HBBO	**2.891**	Human Behavior-Based Optimization
FPA	3.115	Flower Pollination Algorithm
PSO	3.026	Particle Swarm Optimizer
BHBO	3.503	Black Hole-Based Optimization [5]

Fig. 3 shows the tendency for reducing the total real power losses objective function using the different techniques. The active power losses obtained with different techniques are shown in table 4 which made sense that the results obtained by HBBO give better values than the other methods. By means of the same settings the results achieved in case 2 with the HBBO technique are compared to some other methods and it displays that the real power transmission losses are greatly reduced compared to FPA and PSO.

Case 3: Minimization of Reactive Power Losses.

The accessibility of reactive power is the main point for static system voltage stability margin to provision the transmission of active power from the source to sinks [5].

Thus, the minimization of *VAR* losses are given by the following expression:

$$J = \sum_{i=1}^{NGen} Q_i = \sum_{i=1}^{NGen} Q_{Gi} - \sum_{i=1}^{NGen} Q_{Di} \quad (28)$$

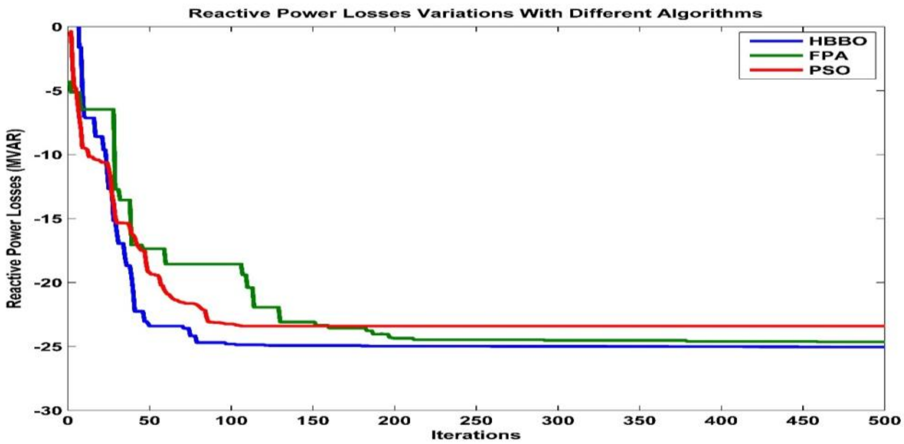

Fig. 4. Reactive Power Losses Variations with Different Algorithms.

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Table 5. Optimal Values of Reactive Power Losses for Different Methods.

Method	**Q_{losses} (MVAR)**	**Method Description**
HBBO	**-25.121**	Human Behavior-Based Optimization
FPA	-25.056	Flower Pollination Algorithm
PSO	-23.407	Particle Swarm Optimizer
BHBO	-20.152	Black Hole-Based Optimization [5]

It is notable that the reactive losses may not essentially positive. The variation of reactive power losses with different methods display in fig. 4. It demonstrates that the suggested method has better convergence characteristics. The statistical values of reactive power losses obtained with different methods are shown in table 5 which displays that the results obtained by HBBO are improvedcompared to other methods. It is clear from the outcomes that the reactive power losses are greatly decreased with respect to FPA and PSO.

Case 4: Voltage Profile Improvement.
Here the goal is to increase voltage profile by reducing the voltage deviation of PQ buses from 1.0 p. u. Hence, the objective function may be calculated as follows [5]:

$$Y_{voltage\_deviation} = \sum_{i=1}^{NGen} |V_i - 1.0| \quad (29$$

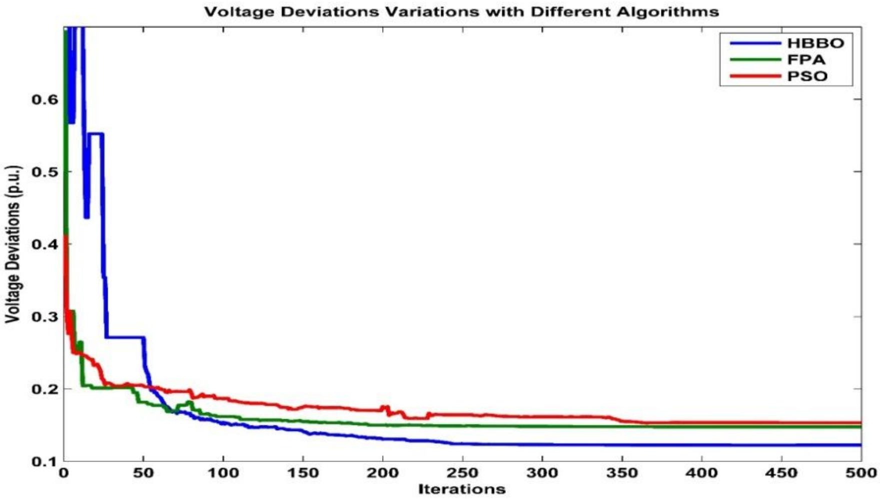

Fig. 5.Voltage Deviations Variations with Different Algorithms.

Table 6.Optimal Values of Voltage Deviations for Different Methods.

Method	**Voltage Deviation (p.u.)**	**Method Description**
HBBO	**0.1063**	Human Behavior-Based Optimization
FPA	0.1845	Flower Pollination Algorithm
PSO	0.1506	Particle Swarm Optimization
DE	0.1357	Differential Evolution [4]
BHBO	0.1262	Black Hole-Based Optimization [5]

Voltage deviation minimization with different algorithm can be shown in fig. 5. The optimal values of voltage deviations for case 4 obtained with HBBO technique is compared with FPA and PSO as shown in table 6. Comparison displays that HBBO gives better minimization of voltage deviation as compared to FPA and PSO.

Case 5: Voltage Stability Enhancement

The system has the capability to retain continuously tolerable bus voltages at every node beneath standard operational environments, next to the rise in load, as soon as the system is being affected by fault. The optimized control variables may cause increasing and unmanageable voltage dip causing a tremendous voltage collapse [5].

Thus, the objective function may be given as:

$$Y_{voltage\_stability\_enhancement} = L_{\max} \qquad (30)$$

The Lmax variations with different algorithm can be shown in fig. 6. The optimal values of Lmax for case 5 obtained with HBBO algorithm is compared with FPA and PSO as shown in table 7. Comparison displays that HBBO give better Lmax value as compared to FPA and PSO.

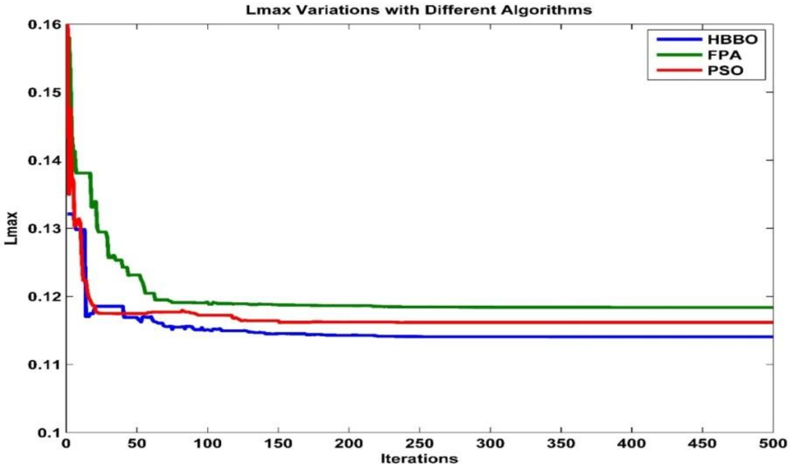

Fig. 6. Lmax Variations with Different Algorithms.

Table 7.Optimal Values of Lmax for Different Methods.

Method	**L_{max}**	**Method Description**
HBBO	**0.1136**	Human Behavior-Based Optimization
FPA	0.1166	Flower Pollination Algorithm
PSO	0.1180	Particle Swarm Optimization
DE	0.1219	Differential Evolution [4]
BHBO	0.1167	Black Hole-Based Optimization [5]

CONCLUSION

In the present work, problem of optimal power flow is optimized for the IEEE 30 bus system using Human Behavior-Based Optimization (HBBO) technique. Five cases are considered in the OPF problem solution that are Fuel cost reduction, Active Power Losses Minimization, Reactive Power Losses Minimization, Voltage Profile Improvement and Voltage Stability Enhancement.

The solutions obtained from the HBBO technique has good convergence characteristics. HBBOgives the competitive results with respect to FPA, PSO and other well-known techniques which confirms the strength of recommended algorithm.

REFERENCES

[1] Duman S, Güvenç U, Sönmez Y, Yörükeren N. Optimal power flow using gravitational search algorithm. Energy Convers Manag 2012;59:86–95.
[2] H.R.E.H. Bouchekara, M.A. Abido, A.E. Chaib, R. Mehasni, Optimal power flow using the league championship algorithm: a case study of the Algerian power system, Energy Convers. Manag. 87 (2014) 58–70.
[3] H.R.E.H. Bouchekara, M.A. Abido, M. Boucherma, Optimal power flow using Teaching-Learning-Based

Optimisation technique, Electr. Power Syst. Res. 114(2014) 49–59.
[4] A.A. Abou El Ela, M.A. Abido, Optimal power flow using differential evolution algorithm, Electr. Power Syst. Res. 80 (7) (2010) 878–885.
[5] H.R.E.H. Bouchekara, Optimal power flow using black-hole-based optimisation approach, Appl. Soft Comput. (2013).
[6] S. Frank, I. Steponavice, S. Rebennack, Optimal power flow: a bibliographic survey I. Formulations and deterministic methods, Energy Syst. 3 (3) (2012)221–258.
[7] M.R. AlRashidi, M.E. El-Hawary, Applications of computational intelligence techniques for solving the revived optimal power flow problem, Electr. PowerSyst. Res. 79 (4) (2009) 694–702.
[8] Seyed-Alireza Ahmadi (2016). The Human Behavior- Based Optimization. Neural Comput & Applic 10.1007/s00521-016-2334-4.
[9] M.A. Abido, Optimal power flow using particle swarm optimisation, Int. J. Electr.Power Energy Syst. 24 (7) (2002) 563–571.
[10] K. Lee, Y. Park, J. Ortiz, A united approach to optimal real and reactive power dispatch, IEEE Trans. Power Appar. Syst. 104 (5) (1985) 1147–1153.
[11] O. Alsac, B. Stot, Optimal load flow with steady-state security, IEEE Trans. PowerApp. Syst. PAS-93 (3) (1974) 745–751