Optimal Power Flow using a hybrid Particle Swarm Optimizer with Moth Flame Optimizer

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Abstract

At present, power system operation, control, Management becomes very complex due to continuously increasing demand. Flexible AC Transmission System (FACTS) controllers are used to increase power transfer capability of the transmission lines closer to their limits. This paper proposed a methodology to solve Optimal Power Flow (OPF) problem in the presence of Thyristor Controlled Series Capacitor (TCSC) while satisfying system operating and practical constraints. A novel cost objective function is formulated by combining investment cost of the TCSC with the conventional fuel cost function. The proposed methodology is tested on standard IEEE-14 bus test system with supporting results.

Index terms— economic dispatch, ramp-rate limit, prohibited operating zones, TCSC, investment cost.

1 Introduction

t the present time, The Optimal power flow (OPF) is a very significant problem and most focused objective for power system planning and operation [1]. The OPF is the elementary tool which permits the utilities to identify the economic operational and secure states in the system [2]. The OPF problem is one of the utmost operating desires of the electrical power system [3]. The prior function of OPF problem is to evaluate the optimum operational state for Bus system by minimizing each objective function within the limits of the operational constraints like equality constraints and inequality constraints [4]. Hence, the optimal power flow problem can be defined as an extremely non-linear and non-convex multimodal optimization problem [5].

From the past few years too many optimization techniques were used for the solution of the Optimal Power Flow (OPF) problem. Some traditional methods used to solve the proposed problem have some limitations like converging at local optima and so they are not suitable for binary or integer problems or to deal with the lack of convexity, differentiability, and continuity [6]. Hence, these techniques are not suitable for the actual OPF situation. All these limitations are overcome by metaheuristic optimization methods. Some of these methods are [7][8][9][10]: genetic algorithm (GA) [11], hybrid genetic algorithm (HGA) [12], enhanced genetic algorithm (EGA) [13][14], differential evolution algorithm (DEA) [15][16], artificial neural network (ANN) [17], particle swarm optimization algorithm (PSO) [18], tabu search algorithm (TSA) [19], gravitational search algorithm (GSA) [20], biogeography based optimization (BBO) [21], harmony search algorithm (HSA) [22], krill herd algorithm (KHA) [23], cuckoo search algorithm (CSA) [24], ant colony algorithm (ACO) [25], bat optimization algorithm (BOA) [26], Ant-lion optimizer (ALO) [27][28] and Multi-Verse optimizer (MVO) [29].

In the present work, a newly introduced hybrid meta-heuristic optimization technique named Hybrid Particle Swarm Optimization-Moth Flame Optimizer (HPSO-MFO) is applied to solve the Optimal Power Flow problem. HPSO-MFO comprises of best characteristic of both Particle Swarm Optimization [30] and Moth-Flame Optimizer [31][32] algorithm. The capabilities of HPSO-MFO are finding the global solution, fast convergence rate due to the use of roulette wheel selection, can handle continuous and discrete optimization problems.

According to No Free Lunch Theorem [27,29,30], particular meta-heuristic algorithm is not best for every problem. So, we considered HPSO-MFO for continues optimal power flow problem based on No Free Lunch Theorem. In this work, the HPSO-MFO is presented to standard IEEE-30 bus test system ??33] to solve the OPF

[34-37] problem. There are five objective cases considered in this paper that have to be optimize using HPSO-MFO technique are Fuel Cost Reduction, Voltage Stability Improvement, Voltage Deviation Minimization, Active Power Loss Minimization and Reactive Power Loss Minimization. The results show the optimal adjustments of control variables in accordance with their limits. The results obtained using HPSO-MFO technique has been compared with Particle Swarm Optimisation (PSO) and Moth Flame Optimizer (MFO) techniques. The results show that HPSO-MFO gives better optimization values as compared to other methods which prove the effectiveness of the proposed algorithm.

This paper is summarized as follow: After the first section of the introduction, the second section concentrates on concepts and key steps of standard PSO and MFO techniques and the proposed Hybrid PSO-MFO technique. The third section presents the formulation of Optimal Power Flow problem. Next, we apply HPSO-MFO to solve OPF problem on IEEE-30 bus system in order to optimize the operating conditions of the power system. Finally, the results and conclusion are drawn in the last section.

2 II. Standard PSO and Standard MFO a) Particle Swarm Optimization

The particle swarm optimization algorithm (PSO) was discovered by James Kennedy and Russell C. Eberhart in 1995 [30]. This algorithm is inspired by the simulation of social psychological expression of birds and fishes. PSO includes two terms ?? ???????? and ?? ???????? . Position and velocity are updated over the course of iteration from these mathematical equations:1 1 1 2 2 ( ) ( ) t t t t t t ij ij v wv c R Pbest X c R Gbest X + = + ? + ? (1) 1 1 t t t X X v + + = + ( ) i 1, 2...NP = And ( ) j 1, 2...NG =**(2)**

Wheremax min max ( )* max w w iteration w w iteration ? = ? ,**(3)**

w max =0.4 and w min =0.9.t ij v , 1 t ij v +

is the velocity of aj th member of ani th particle at iteration number (t) and (t+1). (Usually C 1 =C 2 =2), r 1 and r 2 Random number (0, 1).

3 b) Moth-Flame Optimizer

A novel nature-inspired Moth-Flame optimization algorithm [31] based on the transverse orientation of Moths in space. Transverse orientation for navigation uses a constant angle by Moths with respect to Moon to fly in straight direction in night. In MFO algorithm that Moths fly around flames in a Logarithmic spiral way and finally converges towards the flame. Spiral way expresses the exploration area and it guarantees to exploit the optimum solution [31]:

Moth-Flame optimizer is first introduced by Seyedali Mirjalili in 2015 [31]. MFO is a populationbased algorithm; we represent the set of moths in a matrix:1,1 1,**2 1, 2,1, 2,2 2, ,1 ,2 , , , , , , , , d d**n n n d m m m m m m M m m m ? ? ? ? ? ? ? ? ? ? = ? ? ? ? ? ? ? ? ? ? ? ? ?**(4)**

Where n represents a number of moths and d represents a number of variables (dimension).

For all the moths, we also assume that there is an array for storing the corresponding fitness values as follows:1 2 . . n OM OM OM OM ? ? ? ? ? ? ? ? = ? ? ? ? ? ? ? ? ? ? (**5**)

Where n is the number of moths. Note that the fitness value is the return value of the fitness (objective) function for each moth. The position vector (first row in the matrix M for instance) of each moth is passed to the fitness function and the output of the fitness function is assigned to the corresponding moth as its fitness function (OM 1 in the matrix OM for instance).

Other key components in the proposed algorithm are flames. We consider a matrix similar to the moth matrix [31]:1, 1 1,**2 1, 2, 1 2, 2 2, , 1 , 2 , ...**. . . . . . d d n n n d FL FL FL FL FL FL F FL FL FL ? ? ? ? ? ? ? ? = ? ? ? ? ? ? ? ?**(6)**

Where n shows a number of moths and d represents a number of variables (dimension).

We know that the dimension of M and F arrays are equal. For the flames, we also assume that there is an array for storing the corresponding fitness values [31]:1 2 . . n OFL OFL OF OFL ? ? ? ? ? ? ? ? = ? ? ? ? ? ? ? ? (**7**)

Where n is the number of moths.

Here, it must be noted that moths and flames both are solutions. The variance among them is the manner we treat and update them, in the iteration. The moths are genuine search agents that move all over the search space while flames are the finest location of moths that achieves so far. Therefore, every moth searches around a flame and updates it in the case of discovering an enhanced solution. With this mechanism, a moth never loses its best solution.

The MFO algorithm is three rows that approximate the global solution of the problems defined like as follows [31]:( ) MFO I, P, T = (8)

I is the function that yields an uncertain population of moths and corresponding fitness values. The methodical model of this function is as follows:{ } : , I M OM ? ? (9)

The P function, which is the main function, expresses the moths all over the search space. This function receives the matrix of M and takes back its updated one at every time with each iteration.: P M M ? (10)

The T returns true and false according to the termination Criterion satisfaction:{ } : , T M true false ? (11)

In order to mathematical model this behavior, we change the location of each Moth regarding a flame with the following equation:

(,)i i j M S M F = (12)

Where indicate the moth, indicates the flame and S is the spiral function.

In this equation flame FL n,d (search agent * dimension) of equation (6) modifies the moth matrix of equation (12).

Considering these points, we define a log (logarithmic scale) spiral for the MFO algorithm as follows [31]:( ) ( ) , * cos 2 bt i j i j S M F D e t F ? = +**(13)**

Where: i D expresses the distance of the moth for thej th flame, b is a constant for expressing the shape of the log (logarithmic) spiral, and t is a random value in [-1, 1].i j i D F M = ?**(14)**

Where: i M represent the i th moth, F j represents the j th flame, and where i D expresses the path length of the i th moth for the j th flame. The no. of flames are adaptively reduced with the iterations. We use the following formulation:1 * N flame no round N l T ? ? ? = ? ? ? ? ? (**15**)

Where l is the present number of iteration, N is the maximum number of flames, and Tshows the maximum number of iterations. O MFO O t O Quick sort O position update = + 2 2 ( ) ((*)) ( ) O MFO O t n n d O tn tnd = + = +( ) ( ) ( ) ( ) ( )

Where n shows a number of moths, t represents maximum no. of iterations, and d represents no. of variables.

4 c) The Hybrid PSO-MFO Algorithm

The drawback of PSO is the limitation to cover small search space while solving higher order or complex design problem due to constant inertia weight. This problem can be tackled with Hybrid PSO-MFO as it extracts the quality characteristics of both PSO and MFO. Moth-Flame Optimizer is used for exploration phase as it uses logarithmic spiral function so it covers a broader area in uncertain search space. Because both of the algorithms are randomization techniques so we use term uncertain search space during the computation over the course of iteration from starting to maximum iteration limit. Exploration phase means the capability of an algorithm to try out a large number of possible solutions. The position of particle that is responsible for finding the optimum solution to the complex non-linear problem is replaced with the position of Moths that is equivalent to the position of the particle but highly efficient to move solution towards optimal one. MFO directs the particles faster towards optimal value, reduces computational time. As we know that that PSO is a well-known algorithm that exploits the best possible solution for its unknown search space. So the combination of best characteristic (exploration with MFO and exploitation with PSO) guarantees to obtain the best possible optimal solution of the problem that also avoids local stagnation or local optima of the problem.

A set of Hybrid PSO-MFO is the combination of separate PSO and MFO. Hybrid PSO-MFO merges the best strength of both PSO in exploitation and MFO in exploration phase towards the targeted optimum solution.1 1 1 2 2 (_) ( ) t t t t t t ij ij v wv c R Moth Pos X c R Gbest X + = + ? + ?**(17)**

III.

5 Optimal Power Flow Problem Formulation

As specified before, OPF is the optimized problem of power flow that provides the optimum values of independent variables by optimizing a predefined objective function with respect to the operating bounds of the system [1]. The OPF problem can be mathematically expressed as a non-linear constrained optimization problem as follows [1]: Minimize f(a,b) (18) Subject to s(a,b)=0**(19)**

6 i. Control variables

The control variables should be adjusted to fulfill the power flow equations. For the OPF problem, the set for control variables can be formulated as [1], [4]:2 1 1 1 [ ] ,

, ,NTr NGen NGen NCom T G G G G C C P P V V Q b Q T T = ? ? ? ?**(21)**

Where, G P = Real power output at the PV(Generator) buses excluding at the slack (Reference) bus.G V = Magnitude of Voltage at PV (Generator) buses. C Q = shunt VAR compensation.

T = tap settings of the transformer.

NGen, NTr, NCom= No. of generator units, No. of tap changing transformers and No. of shunt VAR compensation devices, respectively. The control variables are the decision variables of the power system which could be adjusted as per the requirement.

7 ii. State variables

There is a need of variables for all OPF formulations for the characterization of the Electrical Power Engineering state of the system. So, the state variables can be formulated as [1], [4]:1 1 1 1] [, , , NLB NGen T l l L L G G G Nline P V V Q Q S S a = ? ? ?**(22)**

Where,

8 b) Constraints

There are two OPF constraints named inequality and equality constraints. These constraints are explained in the sections given below.

9 i. Equality constraints

The physical condition of the power system is described by the equality constraints of the system. These equality constraints are basically the power flow equations which can be explained as follows [1], [4].

10 a. Real power constraints

The real power constraints can be formulated as follows:[( ) ( )] 0 NB i j ij ij ij Di Gi J i ij P P V V G Cos B Sin ? ? = ? ? + = ? (23) b. Reactive power constraints [( ) ( )] 0 NB i j ij ij ij ij Di Gi J i Q Q V V G Cos B Sin ? ? = ? ? + = ?**(24)**

Where,j ij i ? ? ? = ?

is the phase angle of voltage between buses i and j.NB= total No. of buses, G P = real power output, G Q = reactive power output, ij ij ij Y G jB = +

shows the susceptance and conductance between bus i and j, respectively, ij Y is the mutual admittance between buses I and j.

11 ii. Inequality constraints

The boundaries of power system devices together with the bounds created to surety system security are given by inequality constraints of the OPF [4], [5].

12 a. Generator constraints

For all generating units including the reference bus: voltage magnitude, real power and reactive power outputs should be constrained within its minimum and maximum bounds as given below [27]:, i i i upper l er G o G G w V V V ? ? i=1,?, NGen (**25**) i i i upper lower G G G P P P ? ? , i=1,?, NGen**(26)**i i i upper lower G G G Q Q Q ? ? , i=1,?, NGen (27)

b. Transformer constraints Tap settings of transformer should be constrained inside their stated minimum and maximum bounds as follows [27]:i i i upper lower G G G T T T ? ? , i=1,?,NGen**(28)**

c. Shunt VAR compensator constraints Shunt VAR compensation devices need to be constrained within its minimum and maximum bounds as given below [27]:i i i upper lower C GC C Q Q Q ? ? , i=1,?,NGen**(29)**

d. Security constraints These comprise the limits of a magnitude of the voltage at PQ buses and loadings on the transmission line. Voltage for every PQ bus should be limited by their minimum and maximum operational bounds. Line flow over each line should not exceed its maximum loading limit. So, these limitations can be mathematically expressed as follows [27]:i i lower upper L L L V V V ? ? , i=1,?,NGen (**30**) i i upper l l S S ? , i=1,?,Nline**(31)**

The control variables are self-constraint. The inequality constrained of state variables comprises the magnitude of PQ bus voltage, active power production at reference bus, reactive power production and loadings on line may be encompassed into an objective function in terms of quadratic penalty terms. In which, the penalty factor is multiplied by the square of the indifference value of state variables and is included in the objective function and any impractical result achieved is declined [27].

Penalty function may be mathematically formulated as follows:

( )1 1 2 2 2 1 1 0 ( ) ( ) i i i i NLB NGen Nline aug P V L L G G Q S l l i i i lim lim max J J P P V V S S = = = = + ? ? + ? ? + ? + ? ? ? ? ? ?**(32)**

Where, , , , The reactive power constraints can be formulated as follows: minimum limit lim U takings the value of that limit. This can be shown as follows [27]:P V Q S = ? ? ? ?

; ;upper upper lim lower lower U U U U U U U = ? > ? < ? (33)

IV.

13 Application and Results

The PSO-MFO technique has been implemented for the OPF solution for standard IEEE 30bus test system and for a number of cases with dissimilar objective functions. The used software program is written in MATLAB R2014b computing surroundings and used on a 2.60 GHz i5 PC with 4 GB RAM. In this work the HPSO-MFO population size is selected to be 40.

14 a) IEEE 30-bus test system

With the purpose of elucidating the strength of the suggested HPSO-MFO technique, it has been verified on the standard IEEE 30-bus test system as displays in fig. 2. The standard IEEE 30-bus test system selected in this work has the following features [6] In addition, generator cost coefficient data, the line data, bus data, and the upper and lower bounds for the control variables are specified in **??**33].

In given test system, five diverse cases have been considered for various purposes and all the acquired outcomes are given in Tables 3, 5, 7, 9, 11. The very first column of this tables denotes the optimal values of control variables found where:

-P G1 through P G6 and V G1 through V G6 signifies the power and voltages of generator 1 to generator 6. -T 4-12 , T 6-9 , T 6-10 and T 28-27 are the transformer tap settings comprised between buses 4-12, 6-9, 6-10 and 28-27.-Q C10 , Q C12 , Q C15 , Q C17 , Q C20 , Q C21 , Q C23 , Q C24 and Q C29

denote the shunt VAR compensators coupled at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. Further, fuel cost ($/hr), real power losses (MW), reactive power losses (MVAR), voltage deviation and Lmax represent the total generation fuel cost of the system, the total real power losses, the total reactive power losses, the load voltages deviation from 1 and the stability index, respectively. Other particulars for these outcomes will be specified in the next sections.

The control parameters for HPSO-MFO, MFO, PSO used in this problem are given in table 1.

In table 1, no. of variables (dim) shows the six no. of generators used in the 30 bus system. It gives the optimization values for different cases as they depends on the decision variables. In all 5 cases, results are the average value obtained after 10 number of runs. The very common OPF objective that is generation fuel cost reduction is considered in the case 1. Therefore, the objective function Y indicates the complete fuel cost of total generating units and it is calculated by following equation [1]:1 ($ /) NGen i i Y f hr = = ? (34)

Where, i f is the total fuel cost of th i generator.

i f , may be formulated as follow: 2 which displays that the results obtained by PSO-MFO are better than the other methods. The optimal values of control variables obtained by different algorithms for case 1 are specified in Table 3. By means of the same settings i.e. control variables boundaries, initial conditions and system data, the results achieved in case 1 with the PSO-MFO technique are compared to some other methods and it display that the total fuel cost is greatly reduced compared to the initial case [6]. Quantitatively, it is reduced from 901.951$/hr to 799.056$/hr. Case 2: Voltage profile improvement Bus voltage is considered as most essential and important security and service excellence indices [6]. Here the goal is to reduce the fuel cost and increase voltage profile simultaneously by reducing the voltage deviation of PQ (load) buses from the unity 1.0 p.u.

15 Fig. 3: Fuel cost variations with different algorithms

Hence, the objective function may be formulated by following equation [4]:cost voltage deviation Y Y wY ? = + (36)

Where, w is an appropriate weighting factor, to be chosen by the user to offer a weight or importance to each one of the two terms of the objective function. cos 1 NGen t i i Y f = = ? (37) _1 | 1.0 | NGen voltage deviation i i Y V = = ? ? (38)

The variation of voltage deviation with different algorithms over iterations is sketched in fig. **??**. It demonstrates that the suggested method has good convergence characteristics. The statistical values of voltage deviation obtained with different methods are shown in table 4 which display that the results obtained by PSO-MFO are better than the other methods excluding GSA method. The optimal values of control variables obtained by different algorithms for case 2 are specified in Table 5. By means of the same settings the results achieved in case 2 with the PSO-MFO technique are compared to some other methods and it display that the voltage deviation is greatly reduced compared to the initial case [6]. It has been made known that the voltage deviation is reduced from 1.1496 p.u. to 0.1056p.u. using PSO-MFO technique.GSA [2] gives better result than the HPSO-MFO method only in case of voltage deviation among five cases. Due to No Free Lunch (NFL) theorem proves that no one can propose an algorithm for solving all optimization problems. This means that the success of an algorithm in solving a specific set of problems does not guarantee solving all optimization problems with different type and nature. NFL makes this field of study highly active which results in enhancing current approaches and proposing new meta-heuristics every year. This also motivates our attempts to develop a new Hybrid meta-heuristic for solving OPF Problem. Case 3: Voltage stability enhancement Presently, the transmission systems are enforced to work nearby their safety bounds, because of cost-effective and environmental causes. One of the significant characteristics of the system is its capability to retain continuously tolerable bus voltages to each node beneath standard operational environments, next to the rise in load, as soon as the system is being affected by disturbance. The unoptimized control variables may cause increasing and unmanageable voltage drop causing a tremendous voltage collapse [6]. Hence, voltage stability is inviting ever more attention. By using various techniques to evaluate the margin of voltage stability, Glavitch and Kessel have introduced a voltage stability index called L-index depends on the viability of load flow equations for every node **??**34]. The L-index of a bus shows the probability of voltage collapse circumstance for that particular bus. It differs between 0 and 1 equivalent to zero load and voltage collapse, respectively.

For the given system with NB, N Gen and NLB buses signifying the total no. of buses, the total no. of generator buses and the total no. of load buses, respectively. The buses can be distinct as PV (generator) buses at the head and PQ (load) buses at the tail as follows [4]:[ ] L L LL LG L bus G G GL GG G I V Y Y V Y I V Y Y V = = ? ? ? ? ? ?? ? ? ? ? ? ? ?? ? ? ? ? ? ? ?? ?**(39)**

Where, LL Y , LG Y , GL Y and GG Y are co-matrix of bus Y . The subsequent hybrid system of equations can be expressed as:[ ] L L LL LG L G G GL GG G H I V V V I H H I H H = = ? ? ? ? ? ?? ? ? ? ? ? ? ?? ? ? ? ? ? ? ?? ?**(40)**

Where matrix H is produced by the partially inverting of bus The matrix H is given by: [ ]1 LL LL LG LL LL GL LL GG GL LL LG Z Z Y H Z Y Y Z Y Y Z Y ? ? ? ? ? = = ? ? ? ? ?**(41)**

Hence, the L-index denoted by j L of bus j is represented as follows:1 1 i j LG i j ji NGen v L H v = = ? ? j=1,2?,NL**(42)**

Hence, the stability of the whole system is described by a global indicator max L which is given by [6], max max( )j L L = j=1,2?,NL**(43)**

The system is more stable as the value of max L is lower.

The voltage stability can be enhanced by reducing the value of voltage stability indicator L-index at every bus of the system. [6]. Thus, the objective function may be given as follows:cos ___t voltage Stability Enhancement Y Y wY = +**(44)**

Where,cos 1 NGen t i i Y f = = ? (45) max ___voltage stability enhancement Y L = (46)

The variation of the Lmax index with different algorithms over iterations is presented in fig. 4. The statistical results obtained with different methods are shown in table 6 which display that PSO-MFO method gives better results than the other methods. The optimal values of control variables obtained by different algorithms for case 3 are given in Table 7. After applying the PSO-MFO technique, it appears from Table 7 that the value of Lmax is considerably decreased in this case compared to initial [6] from 0.1723 to 0.1126. Thus, the distance from breakdown point is improved.

16 Case 4: Minimization of active power transmission losses

In the case 4 the Optimal Power Flow objective is to reduce the active power transmission losses, which can be represented by power balance equation as follows [6]: 9. By means of the same settings the results achieved in case 4 with the PSO-MFO technique are compared to some other methods and it display that the real power transmission losses are greatly reduced compared to the initial case [6]

17 Case 5: Minimization of reactive power transmission losses

The accessibility of reactive power is the main point for static system voltage stability margin to support the transmission of active power from the source to sinks [6].

Thus, the minimization of VAR losses are given by the following expression:1 1 1 i Gi Di NGen NGen NGen i i i J Q Q Q = = = = = ? ? ? ?**(48)**

It is notable that the reactive power losses are not essentially positive. The variation of reactive power losses with different methods shown in fig. 6. It demonstrates that the suggested method has good convergence characteristics. The statistical values of reactive power losses obtained with different methods are shown in table 10 which display that the results obtained by hybrid PSO-MFO method are better than the other methods. The optimal values of control variables obtained by different algorithms for case 5 are given in Table 11. It is shown that the reactive power losses are greatly reduced compared to the initial case [6] from -4.6066 MVAR to -25.335MVAR using hybrid PSO-MFO method. Table 12 show the comparison of elapsed time taken by the different methods to optimize the different objective cases. The comparison shows that the time taken by all three algorithms is not same which indicates the different evaluation strategy of different methods. V.

18 Robustness Test

In order to check the robustness of the HPSO-MFO for solving continues Optimal Power Flow problems, 10 times trials with various search agents for cases Case 1, Case 2, Case 3, Case 4 and Case 5. Table 2, Table 3, Table 4, Table 5, Table 6, Table 7, Table 8, Table 9, Table 10 and Table 11 presents the statistical results achieved by the HPSO-MFO, MFO and PSO algorithms for OPF problems for various cases. From these tables, it is clear that the optimum objective function values obtained by HPSO-MFO are near to every trial and minimum compare to MFO and PSO algorithms. It proves the robustness of hybrid PSO-MFO algorithm (HPSO-MFO) to solve OPF problem.

19 VI.

20 Conclusion

Particle Swarm Optimization-Moth Flame Optimizer (PSO-MFO), Moth Flame Optimizer and Particle Swarm Optimization Algorithm are successfully applied to standard IEEE 30-bus test systems to solve the optimal power flow problem for the various types of cases. The results give the optimal settings of control variables with different methods which demonstrate the effectiveness of the different techniques. The solutions obtained from the hybrid PSO-MFO method approach has good convergence characteristics and gives the better results compared to MFO and PSO methods which confirm the effectiveness of proposed algorithm.

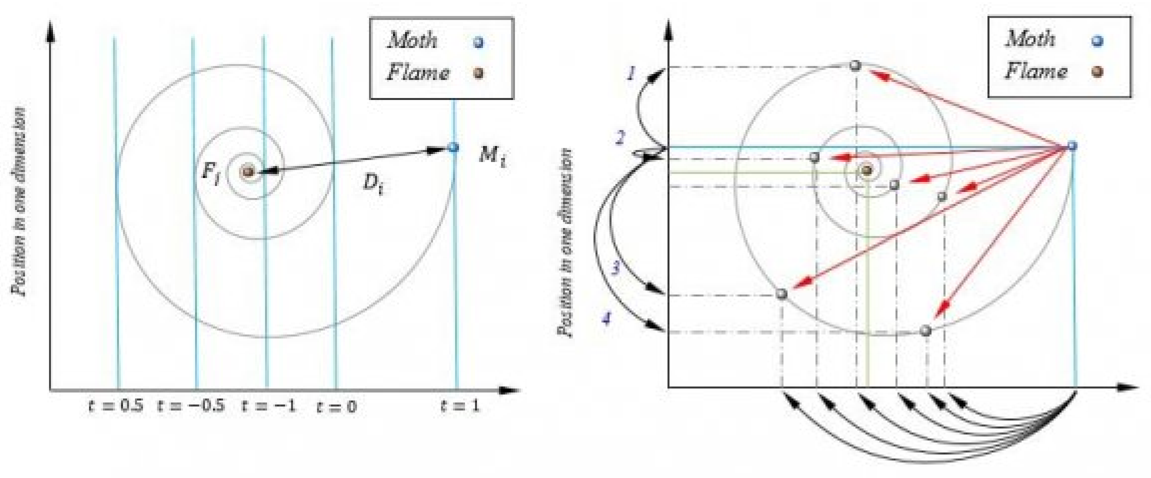

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Figure 1: Fig. 1 :

327 VII. [1] [2] [3] [4] [5] [6] [7] [8] [9] [10]

[1] Year 2017 F Optimal Power Flow using a hybrid Particle Swarm Optimizer with Moth Flame Optimizer

[2] G P = Real power generation at reference bus.© 2017 Global Journals Inc. (US)Global Journal of Researches in Engineering

[3] © 2017 Global Journals Inc. (US)

[4] weighting function (w) 0.65© 2017 Global Journals Inc. (US)Global Journal of Researches in Engineering

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[7] Year 2017 F Optimal Power Flow using a hybrid Particle Swarm Optimizer with Moth Flame Optimizer

[8] Year 2017 F Optimal Power Flow using a hybrid Particle Swarm Optimizer with Moth Flame Optimizer

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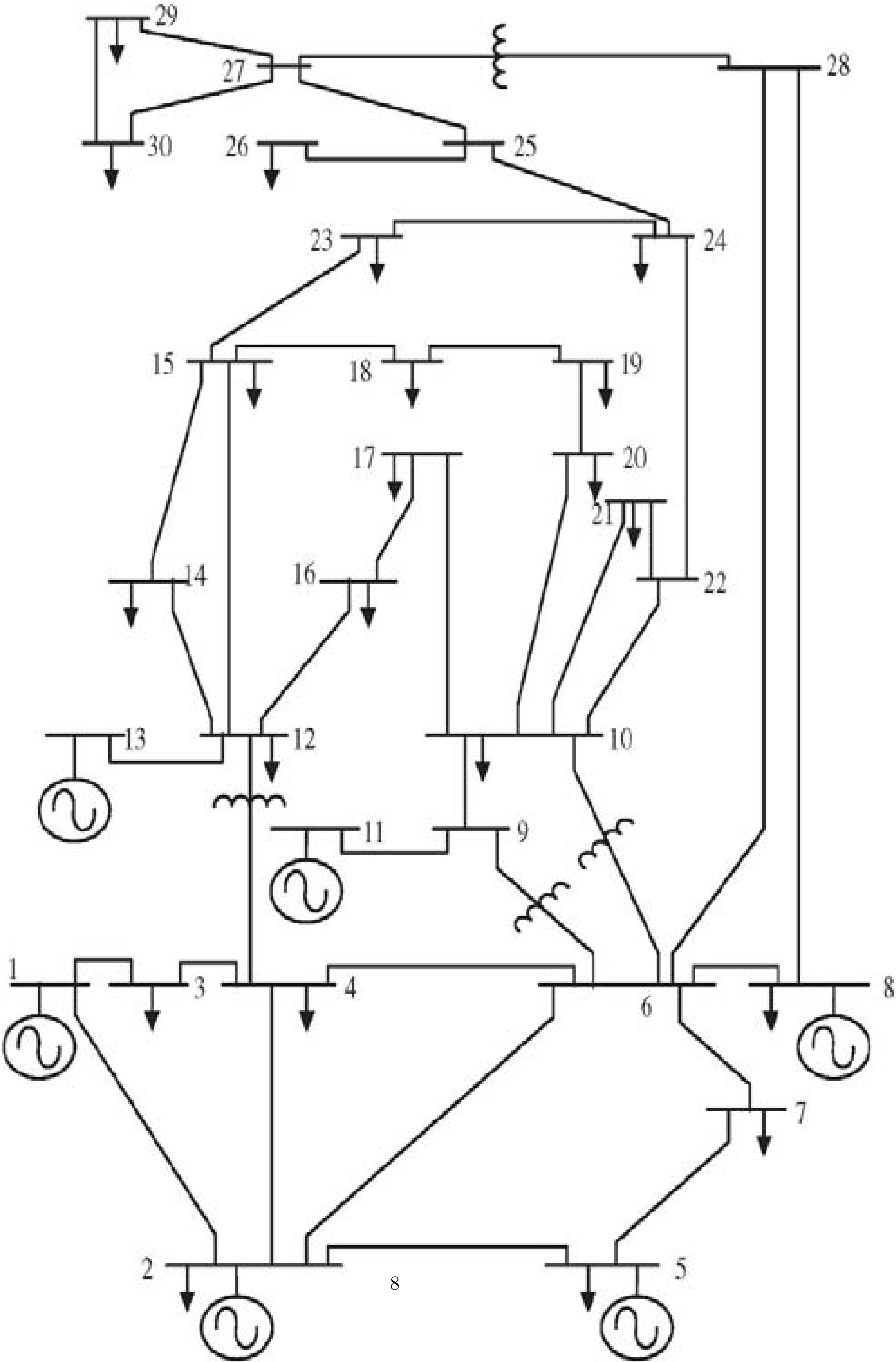
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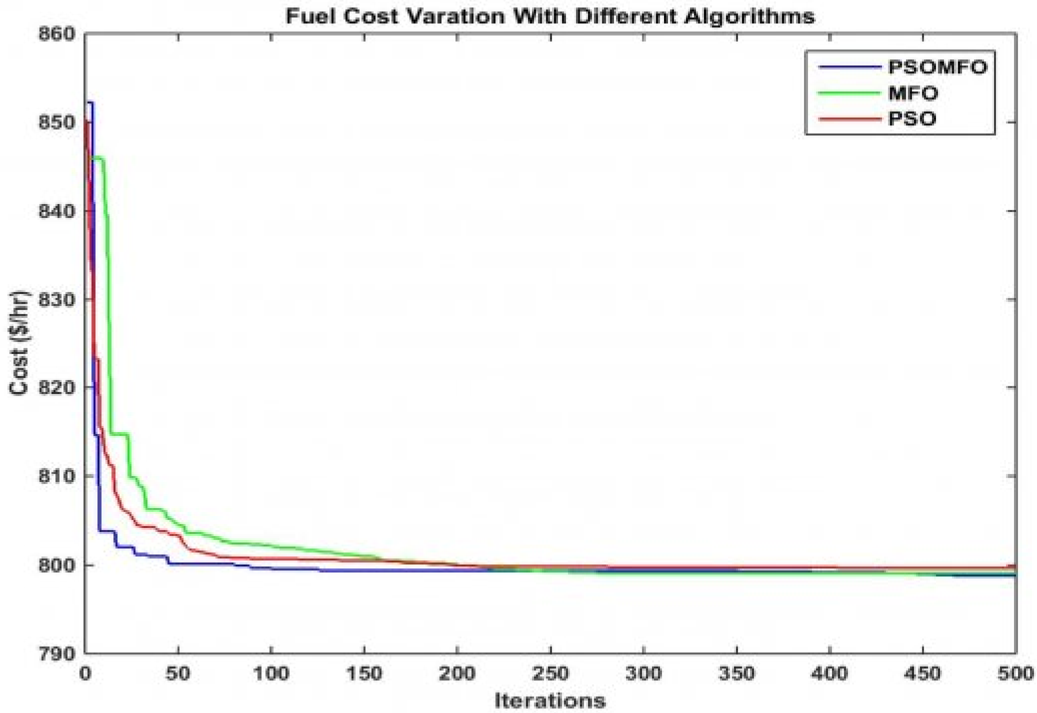


Figure 3: LV=

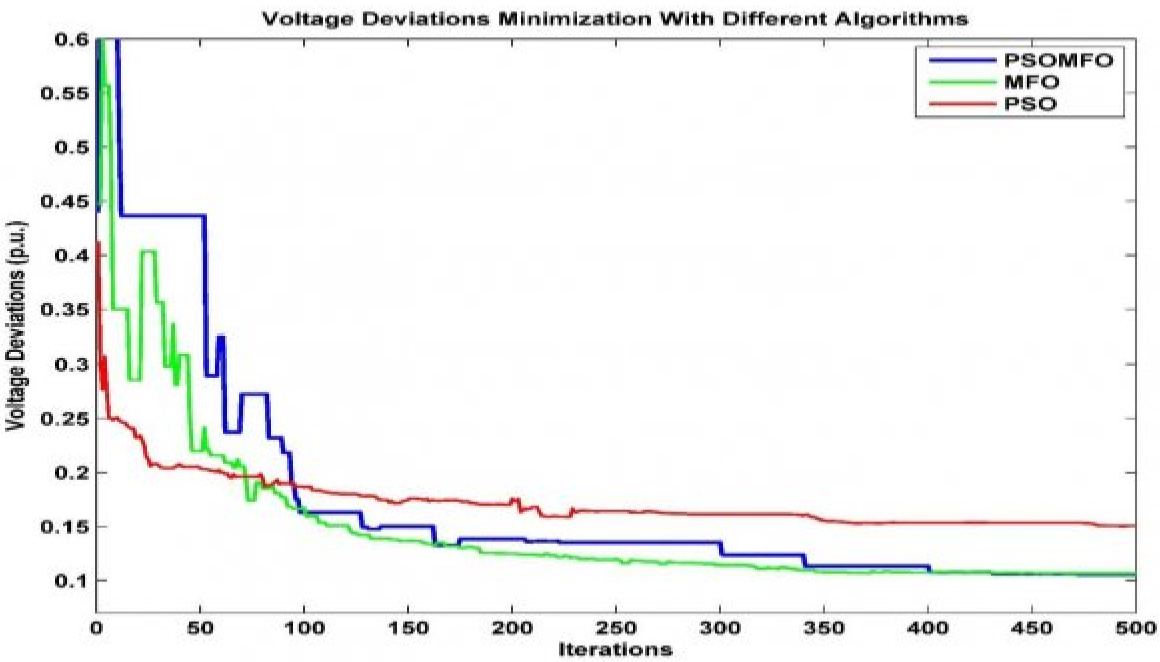


Figure 4: DP

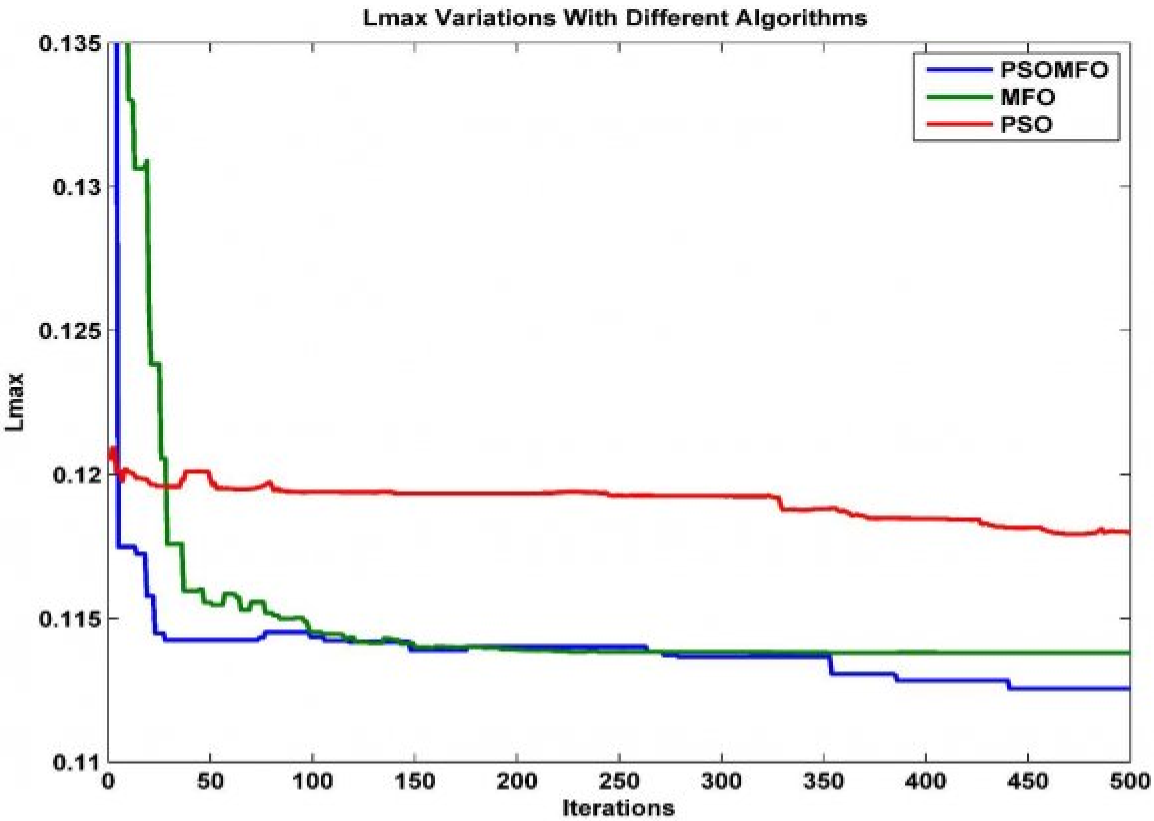
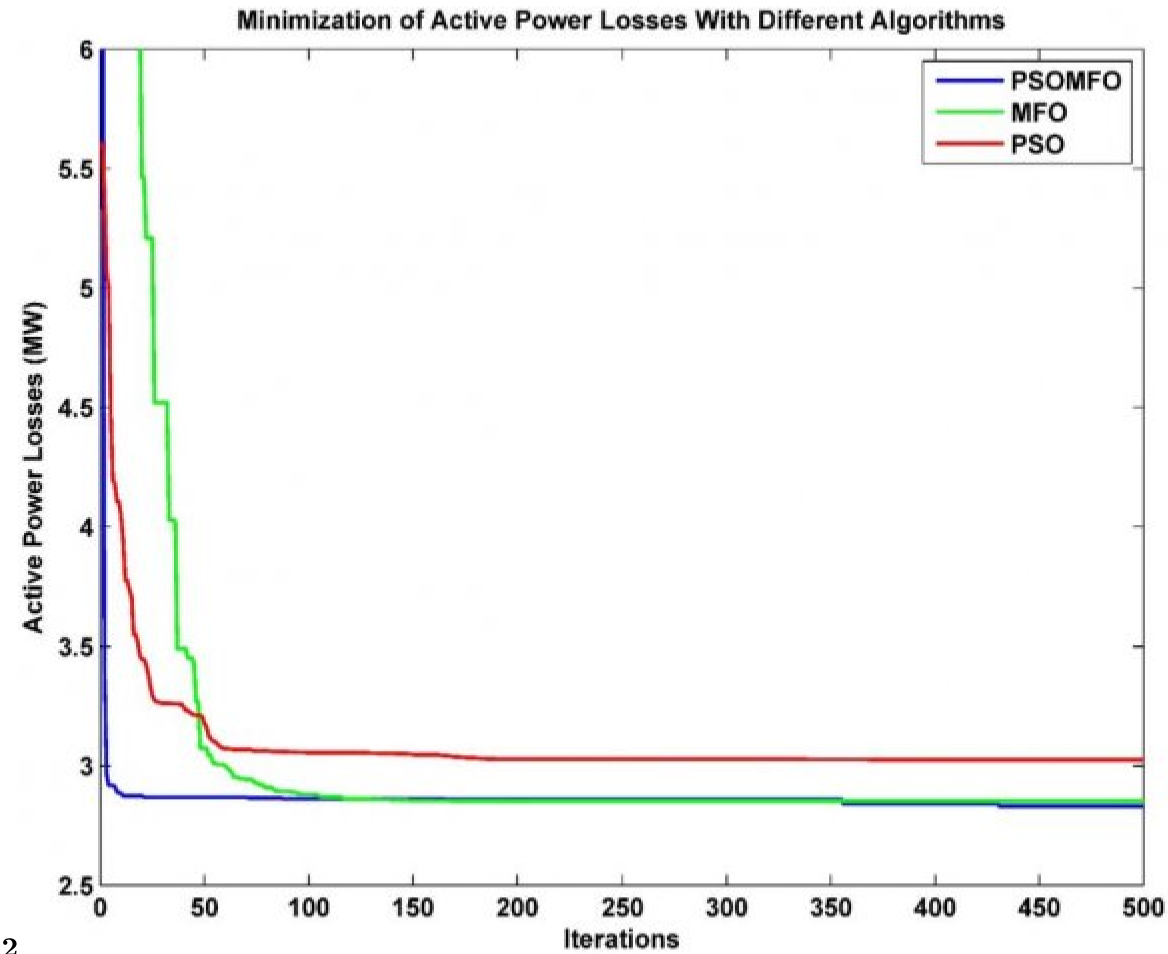

Lmax Variations With Different Algorithms
PSOMFO
MFO
PSO
Lmax
Iterations
0.135
0.13
0.125
0.12
0.115
0.11
0
50
100
150
200
250
300
350
400
450
500

Figure 5:



2

Figure 6: Fig. 2 :

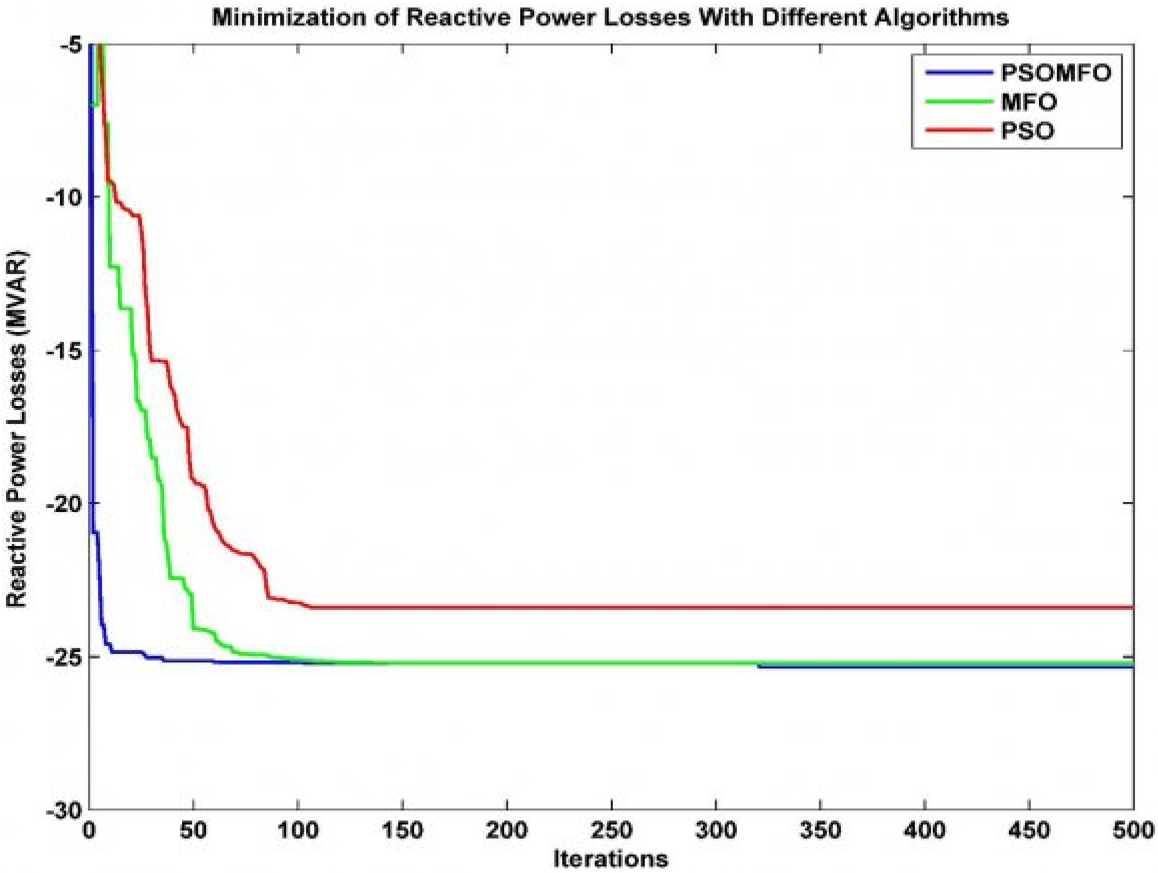


Figure 7: costY

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[Note: penalty factors lim U = Boundary value of the state variable U.If U is greater than the maximum limit, lim U takings the value of this one, if U is lesser than the]

Figure 8:

1

Sr. No.	Parameters	Value
1	Population (No. of Search agents) (N)	40
2	Maximum iterations count (t)	500
3	No. of Variables (dim)	25
4	Random Number	[0,1]
5	source acceleration coefficient (??_1, ??_2)	2

Figure 9: Table 1 :

2

Method	Fuel Cost ($/hr)	Method Description
HPSO-MFO	799.056	Hybrid Particle Swarm Optimization-Moth Flame Optimizer
MFO	799.072	Moth Flame Optimizer
PSO	799.704	Particle Swarm Optimization
DE	799.289	Differential Evolution [15]
BHBO	799.921	Black Hole-Based Optimization [6]

Figure 10: Table 2 :

3

Control Variable	Min	Max	Initial	HPSO-MFO	MFO	PSO
P G1	50	200	99.2230	178.133	177.055	177.105
P G2	20	80	80	48.956	48.698	48.748
P G5	15	50	50	21.385	21.304	21.318
P G8	10	35	20	21.706	21.084	20.986
P G11	10	30	20	10.000	11.883	12.049
P G13	12	40	20	12.000	12.000	12.000
V G1	0.95	1.1	1.05	1.100	1.100	1.100
V G2	0.95	1.1	1.04	1.088	1.088	1.088
V G5	0.95	1.1	1.01	1.062	1.062	1.061
V G8	0.95	1.1	1.01	1.070	1.069	1.070
V G11	0.95	1.1	1.05	1.100	1.100	1.100
V G13	0.95	1.1	1.05	1.100	1.100	1.100
T 4-12	0	1.1	1.078	0.939	1.044	0.976
T 6-9	0	1.1	1.069	1.100	0.900	0.975

Figure 11: Table 3 :

4

Method	Voltage Deviation (p.u)	Method Description
HPSO-MFO	0.1056	Hybrid Particle Swarm Optimization-Moth Flame Optimizer
MFO	0.1065	Moth Flame Optimizer
PSO	0.1506	Particle Swarm Optimization
GSA	0.0932	Gravitational Search Algorithm [2]
DE	0.1357	Differential Evolution [15]
BHBO	0.1262	Black Hole-Based Optimization [6]

Figure 12: Table 4 :

5

Control Variable	Min	Max	Initial	HPSO-MFO	MFO	PSO
P G1	50	200	99.2230	177.650	180.212	175.922
P G2	20	80	80	49.092	49.584	46.389
P G5	15	50	50	15.000	15.000	21.597
P G8	10	35	20	10.000	24.349	19.396
P G11	10	30	20	30.000	12.657	17.656
P G13	12	40	20	12.000	12.000	12.000
V G1	0.95	1.1	1.05	1.033	1.033	1.047
V G2	0.95	1.1	1.04	1.017	1.017	1.034
V G5	0.95	1.1	1.01	1.015	1.005	0.999
V G8	0.95	1.1	1.01	0.997	0.999	1.005
V G11	0.95	1.1	1.05	1.047	1.071	0.999
V G13	0.95	1.1	1.05	1.016	1.052	1.018
T 4-12	0	1.1	1.078	1.065	1.100	0.954
T 6-9	0	1.1	1.069	0.914	0.900	0.969
T 6-10	0	1.1	1.032	0.973	1.072	0.989

Figure 13: Table 5 :

6

Method	L max	Method Description
HPSO-MFO	0.1126	Hybrid Particle Swarm Optimization-Moth Flame Optimizer
MFO	0.1138	Moth Flame Optimizer
PSO	0.1180	Particle Swarm Optimization
GSA	0.1162	Gravitational Search Algorithm [2]
DE	0.1219	Differential Evolution [15]
BHBO	0.1167	Black Hole-Based Optimization [6]

Figure 14: Table 6 :

7

Control Variable	Min	Max	Initial	HPSO-MFO	MFO	PSO
P G1	50	200	99.2230	182.308	177.299	158.331
P G2	20	80	80	45.360	48.792	49.050
P G5	15	50	50	21.109	21.316	18.956
P G8	10	35	20	21.557	20.351	31.224
P G11	10	30	20	10.000	12.370	15.906
P G13	12	40	20	12.000	12.012	17.801
V G1	0.95	1.1	1.05	1.100	1.100	1.098

Figure 15: Table 7 :

8

Method	Active Power Loss (MW)	Method Description
HPSO-MFO	2.831	Hybrid Particle Swarm Optimization-Moth Flame Optimizer
MFO	2.853	Moth Flame Optimizer
PSO	3.026	Particle Swarm Optimization
BHBO	3.503	Black Hole-Based Optimization [6]

Figure 16: Table 8 :

9

Control Variable	Min	Max	Initial	HPSO-MFO	MFO	PSO
P G1	50	200	99.2230	51.269	51.253	51.427
P G2	20	80	80	80.000	80.000	80.000
P G5	15	50	50	50.000	50.000	50.000
P G8	10	35	20	35.000	35.000	35.000
P G11	10	30	20	30.000	30.000	30.000
P G13	12	40	20	40.000	40.000	40.000
V G1	0.95	1.1	1.05	1.100	1.100	1.100
V G2	0.95	1.1	1.04	1.100	1.098	1.100
V G5	0.95	1.1	1.01	1.082	1.080	1.083
V G8	0.95	1.1	1.01	1.086	1.087	1.090
V G11	0.95	1.1	1.05	1.100	1.100	1.100
V G13	0.95	1.1	1.05	1.100	1.100	1.100
T 4-12	0	1.1	1.078	1.044	1.056	0.977
T 6-9	0	1.1	1.069	0.901	0.900	1.100
T 6-10	0	1.1	1.032	0.993	0.982	1.100
T 28-27	0	1.1	1.068	0.987	0.973	0.998
QC 10	0	5	0	5.000	5.000	4.065
QC 12	0	5	0	4.570	5.000	0.000
QC 15	0	5	0	4.969	3.070	5.000
QC 17	0	5	0	4.942	5.000	5.000
QC 20	0	5	0	4.337	5.000	0.000
QC 21	0	5	0	5.000	5.000	5.000
QC 23	0	5	0	5.000	5.000	5.000
QC 24	0	5	0	5.000	5.000	0.000
QC 29	0	5	0	2.412	2.508	0.000
PLoss (MW)	-	-	5.8219	2.831	2.853	3.026

Figure 17: Table 9 :

10

Method	Reactive Power Loss (MVAR)	Method Description
HPSO-MFO	-25.335	Hybrid Particle Swarm Optimization-Moth Flame Optimizer
MFO	-25.204	Moth Flame Optimizer
PSO	-23.407	Particle Swarm Optimization
BHBO	-20.152	Black Hole-Based Optimization [6]

Figure 18: Table 10 :

12

Case No.		Elapsed Time (Seconds)	
	MFO	PSO	HPSO-MFO
1	166.2097	250.2674	211.7915
2	191.8238	266.5375	229.6873
3	196.6275	270.3358	243.2919
4	161.6395	248.8739	259.9731
5	173.5987	253.3971	209.4387

Figure 19: Table 12 :

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