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Optimal power flow using Hybrid Particle Swarm Optimization and Moth Flame Optimizer approach

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Abstract

In this study, the most common problem of the current power system named optimal power flow (OPF) is optimized using the recently hybrid meta-heuristic optimization technique Particle Swarm Optimization-Moth Flame Optimizer (PSO-MFO) algorithm. Hybrid PSO-MFO is an incorporation of PSO used for exploitation stage and MFO for exploration stage in an uncertain environment. The position and velocity of the particle are restructured according to Moth and flame location in each iteration. The hybrid PSO-MFO technique is carried out to solve the OPF problem. The performance of this technique is deliberated and evaluated on the standard IEEE 30-bus and IEEE 57-bus test system. The problems considered in the OPF are fuel cost reduction, Voltage stability enhancement and Active power loss minimization. The results obtained with hybrid PSO-MFO technique is compared with original PSO and MFO.

Key-words: optimal power flow; Particle Swarm Optimization; Moth Flame Optimizer; constraints.

Résumé

Dans cette étude, le problème le plus commun du système de puissance moderne est appelé écoulement de puissance optimale (OPF) est optimisé à utiliser du nouvel algorithme d'optimisation méta-heuristique hybride Optimisation de l'essaim de particules - Optimisation de la flamme papillon (PSO-MFO). Le PSO-MFO hybride est une incorporation de PSO utilisé pour la phase d'exploitation et de MFO pour la phase d'exploration dans un environnement incertain. La position et la vitesse de la particule sont restructurées en fonction de l'emplacement du papillon et de la flamme à chaque itération. La technique hybride PSO-MFO est réalisée pour résoudre le problème OPF. Les performances de cette technique sont délibérées et évaluées sur le système de test standard IEEE 30-bus et IEEE 57-bus. Les problèmes pris en compte dans l'OPF sont la réduction du coût du carburant, amélioration de la stabilité de la tension et la réduction de la perte de puissance active. Les résultats obtenus avec la technique hybride PSO-MFO sont comparés avec les PSO et MFO d'origine.

Mots-clés : écoulement de puissance optimale ; Optimisation de l'essaim de particules ; Optimisation de la

flamme papillon ; contraintes.

1. Introduction

At the existent time, The Optimal power flow (OPF) is a highly important problem and most significant objective for power system planning and operation. The OPF is the basic tool that enables the utilities to identify the economic operational and secure conditions of the system. The OPF problem is one of the greatest operating requests of the power system [1]. The former function of OPF problem is to evaluate the optimal operational state of the Bus system by reducing all objective function within the restrictions of the operational constraints such as equality constraints and inequality constraints [2]. Thus, the optimal power flow problem can be described as a highly non-linear and non-convex multimodal optimization problem [3].

In recent years, too several optimization methods were used to solve the problem of the optimal power flow (OPF). Some conventional techniques used to solve the suggested problem have some restrictions, such as convergence at local optimums, and are therefore not appropriate for binary or integer problems or for dealing with lack of continuity, convexity, and differentiability [4]. Thus, these methods are not appropriate for the actual OPF situation. All these restrictions are overcome by metaheuristic optimization techniques. Some of these techniques are: Krill Herd Algorithm (KHA) [5] ,Artificial Bee Colony (ABC) algorithm[6], Improved Colliding Bodies Optimization (ICBO) algorithm [7], Differential Search Algorithm (DSA)[8], Multi-Objective forced initialized Differential Evolution Algorithm(MO-DEA) [9],Lévy mutation Teaching–Learning-Based Optimization (LTLBO) algorithm [10], Hybrid Shuffle Frog Leaping Algorithm and Simulated Annealing (HSFLA-SA) [11], Hybrid Modified Particle Swarm Optimization and the Shuffle Frog Leaping algorithms (HMPSO-SFLA) [12], and hybrid of Imperialist Competitive Algorithm and Teaching Learning Algorithm (MICA–TLA) [13].

In the current work, a recently inserted hybrid meta-heuristic optimization method called Hybrid Particle Swarm Optimization-Moth Flame Optimizer (PSO-MFO) is utilized to solve the Optimal Power Flow problem. The abilities of PSO-MFO are to finding the global solution; the rapid convergence rate because of the use of the roulette wheel selection can treat discrete and continuous optimization problems. In this study, the PSO-MFO is carried out to standard IEEE-30 bus test system to solve the OPF problem. There are two objective cases take into account in this work that has to be optimize using PSO-MFO method are Fuel Cost Reduction, Active Power Loss Minimization. The result presents the optimal adaptations of control variables in accordance with their restriction. The results yielded using PSO-MFO method has been compared with original PSO and MFO algorithms. The results appeared that PSO-MFO gives better optimization values as compared to other techniques which prove the performance of the suggested method. The rest of the paper organize as follows: Section 1 includes Introduction, Section 2 contains a description of PSO, MFO, and PSO-MFO algorithms, Section 3 consists of simulation results analysis of OPF problem finally conclusion of this paper.

2. Optimal Power Flow formulation

The OPF is a power flow problem that provides the optimal settings of the control variables for specific settings of the load by means of reducing a predefined objective function such as the cost of real power generation or transmission losses. OPF can be formulated as a nonlinear constrained optimization problem as follows:

Minimize: $J\,(x,u)$ (1)

$$g\,(x,u)\le 0$$

$$h\,(x,u)=0$$

Where J *(x, u),* objective function; *h (x, u)*, set of equality constraints; g*(x, u),* set of inequality constraints. U the vector of control variables; x the vector of state variables;

Control variables:

the control variables vector (U) can be expressed as next :

$$u=\left[P_{G_2}\cdots P_{G_{NG}},V_{G_1}\cdots V_{G_{NG}},Q_{C_1}\cdots Q_{C_{NC}},T_1\cdots T_{NT}\right] \quad (2)$$

Where NG the generators' number ,NT and NC are the regulatory transformers' number and the VAR shunt compensators' number, respectively.

State variables:

The state X vector can be formulated in the next:

$$x=\left[P_{G_1},V_{L_1}..V_{L_{NL}},Q_{G_1}..Q_{G_{NG}},S_{l_1}..S_{l_{nl}}\right] \quad (3)$$

Where NL, NG, SL and NTL are the load buses' number, the generators' number,

The transmission line's loading and the transmission lines' number, respectively.

Constraints:

1. Equality constraints

The power equilibrium constraints represent the equilibrium of real and reactive powers. These constraints are formulated as follows:

a) Real power constraints:

$$P_{G_i}-P_{D_i}-V_i\sum_{j=1}^{NB}V_j\left[G_{ij}\cos\left(\delta_{ij}\right)+B_{ij}\sin\left(\delta_{ij}\right)\right]=0 \quad (4)$$

b) Reactive power constraints:

$$Q_{G_i}-Q_{D_i}-V_i\sum_{j=1}^{NB}V_j\left[G_{ij}\sin\left(\delta_{ij}\right)+B_{ij}\cos\left(\delta_{ij}\right)\right]=0 \quad (5)$$

2. Inequality constraints:

The constraints of operational inequality include the next constraints

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \forall i \in NG \quad (6)$$

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \forall i \in NG \quad (7)$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \forall i \in NG \quad (8)$$

$$T_j^{\min} \le T_j \le T_j^{\max} \forall j \in NT \quad (9)$$

$$Q_{C_k}^{\min} \le Q_{C_k} \le Q_{C_k}^{\max} \forall k \in NC \quad (10)$$

3. Security constraints:

$$V_{L_p}^{\min} \le V_{L_p} \le V_{L_p}^{\max} \forall p \in NL \quad (11)$$

$$S_{l_q} \le S_{l_q}^{\max} \forall q \in nl \quad (12)$$

4. Particle Swarm Optimization:

The particle swarm optimization algorithm (PSO) is a stochastic population-based optimization technique which was firstly suggested by Kennedy and Eberhart [14], it is inspired by collective conduct of organisms like flocks of birds, PSO includes two terms P_{best} and G_{best} ,Position and speed are updated through the course of iteration from these following equations:

$$v_{ij}^{t+1} = wv_{ij}^{t} + c_1 r_1 \left(Pbest^t - X^t\right) + c_2 r_2 \left(Gbest^t - X^t\right) \quad (13)$$

$$X^{t+1} = X^t + v^{t+1} \quad i=1,2....NP \quad j=1,2....NG \quad (14)$$

Were

$$w = w^{\max} - \frac{\left(w^{\max} - w^{\min}\right) * iteration}{\max iteration} \quad (15)$$

v_{ij}^{t+1}, v_{ij}^{t} is the speed of j^{th} member of i^{th} particle at iteration number, r_1 and r_2 are two random values within [0, 1]

5. Moth-Flame Optimizer:

In 2015 Seyedali Mirjalili is developed novel technique is named Moth-Flame Optimizer[15],A new Moth-Flame optimization algorithm inspired by nature was based on the transverse orientation of moths in space. The MFO technique is three-rows that approximate the global solution of the problems defined such as follows:

$$\text{Moth Flame Optimizer} = \left[I, P, T\right], \quad (16)$$

I is the function that yield an uncertain population of moths and corresponding fitness values. Considering these points, we define a log (logarithmic scale) spiral for the MFO technique as follows:

$$S\left(M_i, F_j\right) = D_i * e^{bt} \cos\left(2\pi t\right) + F_j \quad (17)$$

Where: D_i Formulate the distance of the moth for the j^{th} flame, b is a constant for Formulating the shape of the log (logarithmic) spiral, and t is a random variable in [-1, 1].

$$D_i = \left|F_j - M_i\right| \quad (18)$$

Where M_i indicate the i^{th} moth, F_j indicates the j^{th} flame, and where D_i formulate the path length of the i^{th} moth for the j^{th} flame.

The number of flames is adaptively reduced over the course of iterations. We use the next expressing:

$$\text{no. of flame} = round\left(N - l * \frac{N-1}{T}\right) \quad (19)$$

Where l indicates the present number of iteration, N indicates the maximum number of flames, and T is the maximum number of iterations.

6. The Hybrid PSO-MFO Algorithm:

A hybrid PSO-MFO is an incorporation of separate PSO and MFO. The disadvantage of PSO is the limitation to cover a small search space while solving a higher order or a complex design problem because of a constant inertia weight .This problem can be handling with the hybrid PSO-MFO because it extracts the quality characteristics of PSO and MFO. Moth-Flame Optimizer is used for the exploration phase because it uses the logarithmic spiral function so it covers broader area in uncertain search space. However, incorporation of best characteristic (exploration with MFO and exploitation with PSO) ensures to gain best possible optimal solution of the problem that as well avoids local stagnation or local optima of problem. Hybrid PSO-MFO incorporates the best capability of both PSO in exploitation and MFO in exploration stage towards the targeted optimum solution.

$$v_{ij}^{t+1} = wv_{ij}^{t} + c_1 r_1 \left(Moth\_Pos^t - X^t\right) + c_2 r_2 \left(Gbest^t - X^t\right) \quad (20)$$

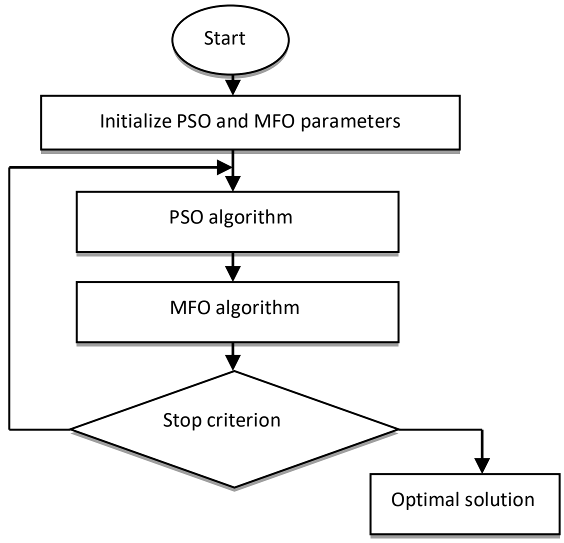

Fig 1. The flowchart of the suggested PSO-MFO method.

7. Simulation results of the IEEE 30-bus test system

The IEEE 30-bus system is employ as the first case study. It has 6 generators and 24 load nodes. The system data and operating terms are given in [60]. The system comprises of 6 generators on buses 1.2, 5, 8, 11 and 13 and 4 control transformers on lines 6-9, 6-10.4-12 and 27-28. In addition, buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 include reactive power sources. The PV buses' voltage magnitudes are taking into consideration in the field of [0.95-1.1 P.U.]. The setting of the control transformers is in the field of voltages at [0.9-1.1 P.U.]. The rank of shunt capacitors in MVAR are between [0-5]. The load buses are subject to admissible operating boundaries [0.95-1.05 P.U.].

The PSO-MFO algorithm has been carried out for the OPF solution for standard IEEE 30-bus test system with two objective functions. The used software program is written in MATLAB R2014a. In this study, the PSO-MFO population size is chosen to be 40.

Case1: Minimization of generation fuel cost

The very common OPF objective that is generation fuel cost decrease is considered in the case 1. Thus, the objective function F indicates the complete fuel cost of total generating units and it is calculated by next equation:

$$J = \sum_{i=1}^{NG} f_i \ (\$/h) \quad (21)$$

Where

$$f_i = \left(a_i + b_i P_{G_i} + c_i P_{G_i}^2\right) \quad (22)$$

where a_i , b_i and c_i are the element, the linear and the quadratic cost coefficients of the *i-th* generator, respectively. The values of these coefficients are presented in [7].

The trend of the total fuel cost with various techniques along iterations is given in Fig. 2. It demonstrates that the proposed technique has outstanding convergence characteristics. The comparisons of fuel cost yielded by Different techniques are presented in Table 2, which displays that the results yielded by PSO-MFO are better than the other techniques. The optimal values of control variables yielded by different methods for case 1 are given in Table1.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 algorithm are compared to some other algorithms.

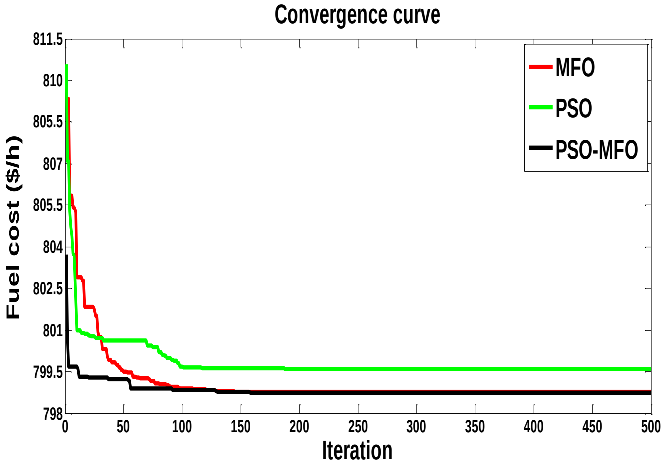

Fig. 2. *Convergent curves of Case 1.*

Case2: Minimization of real power losses

In this case, the Optimal Power Flow objective is to decrease the real power transmission losses, which can be formulated by power balance equation as next:

$$f(x,u) = P_{loss} = \sum_{i=1}^{nl} \sum_{j=1, j\neq i}^{nl} G_{ij} \left[V_i^2 + V_j^2 - 2V_i V_j \cos\left(\delta_{ij}\right)\right] \quad (23)$$

Fig. 3 appear the tendency for decreasing the total active power losses objective function using the various methods. The active power losses obtained by different methods are given in Table 2. This made sense that the result yielded by PSO-MFO gives better solution than the other technique. The optimal values of control variables yielded by different techniques for case 2 are presented in Table1. By means of the same settings, the results achieved in case 2 with the PSO-MFO algorithm are compared to some other techniques.

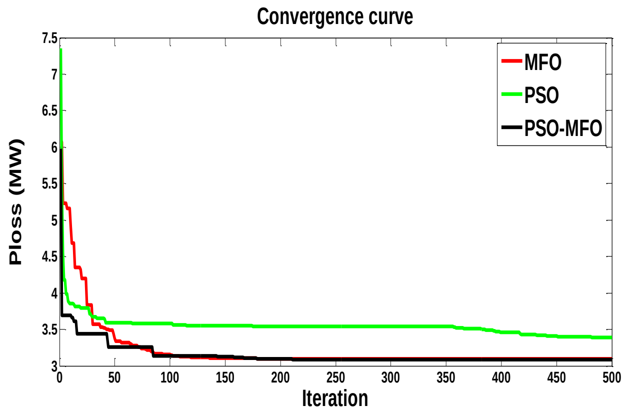

Fig. 3. *Convergent curves of Case*

Case 3: Minimisatin fuel cost with Voltage stability enhancement:

Voltage stability is described as the capability to fix the voltage magnitude of the load buses at a required value or interval in nominal conditions. usually, the voltage stability, at any bus varies between zero (no load case) and one (voltage collapse). Voltage stability index is utilized to estimate the voltage problems of power systems most precisely so as to move the system outlying from voltage collapse state. so as to enhance the voltage stability and move the system outlying from the voltage collapse point, the next objective function is suggested.

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG}a_i+b_iP_{G_i}+c_iP_{G_i}^2\right)+\lambda_L\times L_{\max} \quad (24)$$

There are definite bus types involved in a power system can be classified as generator (PV and slack bus) and load (PQ) buses. Because of the voltage stability and safety problem associated related to reactive power dispatch, it is absolutely needful to distinguish whole of the buses. The L-index expression utilized it this study is also presented as follows:

$$L_j=\left|1-\sum_{i=1}^{NG}F_{ji}\frac{V_i}{V_j}\right| \text{,where } j=1,2,...,NL \quad (25)$$

and $$F_{ji}=-\left[Y_{LL}\right]^{-1}\left[Y_{LG}\right]$$

where, Y_{LL} and Y_{LG} sub-matrices and are gotten from YBUS system matrix after separating load (PQ) buses and generator (PV) buses as shown in (29).

$$\begin{bmatrix}I_L\\I_G\end{bmatrix}=\begin{bmatrix}Y_{LL} & Y_{LG}\\Y_{GL} & Y_{GL}\end{bmatrix}\begin{bmatrix}V_L\\V_G\end{bmatrix} \quad (26)$$

$$L_{\max}=\max\left(L_j\right) \quad \text{j=1,2,......NL} \quad (27)$$

The indicator $L_{\max}$ varies between 0 and 1 where the lower the indicator, the more the system stable. Thus, enhancing voltage stability can be obtained by the minimization of $L_{\max}$ in this case , a further set of objectives was deliberated : decreasing fuel costs and enhancement voltage stability . Hence These objectives have been optimized simultaneously applied the suggested techniques. Table 1 display the best compromising solutions yielded for this case. The suggested PSO-MFO efficiency better than the suggested PSO and MFO technique in terms of solution optimality. Figure 3 appears that the proposed PSO-MFO techniques can provide and have a greater convergence towards the global optimal set than PSO and MFO. For further validation, the yielded best compromising solutions applied the suggested techniques were compared to those found by the other heuristic optimization techniques given in Table 2. Further, the comparison confirms the excellence of the suggested techniques over the previous techniques in terms of solution optimality and possibility.

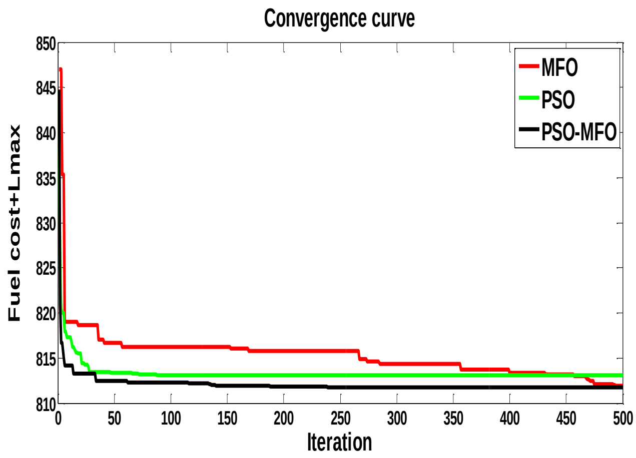

Fig. 4. *Convergent curves of Case 3*

IEEE 57-bus test system

In this section, so as to evaluate the efficiency and ability of suggested FKH in solving multi-objective OPF problem in considerable power systems, a standard IEEE 57-bus power system [20] has been deliberated. The IEEE 57 bus test system comprise of 7generators on buses 1, 2, 3, 6, 8, 9 and 12 and 80 transmission lines [20].

The shunt reactive power sources are take into account at buses 18, 25 and 53 and the total system load demand of 1250.8 MW and 336.4 MVAR, and 15 branches under load tap setting transformer branches [20].

Case4: Fuel cost minimization

In this case the suggested technique PSO-MFO is applied to 57-bus test system so as to reduce the fuel cost. The objective function are presented in equation (22) ,Hence the fuel cost is decrease to 41667.1586 $/h as given in table 3. and best convergence characteristic shown in Fig 4.The yielded set solution to a better than original MFO,PSO and other algorithms. The result comparison obtained by PSO-MFO,MFO and PSO with other algorithms are presented in table 4.

Case 5. Voltage stability enhancement with fuel cost

The suggested PSO-MFO technique is using to another multi-objective function, the reduction of the voltage stability with the fuel cost presented by (24), where w is selected as 100,The optimal values of control variables obtained by different techniques for case 5 are presented in Table 3. best convergence characteristic appears in Fig 5.and a better result is done when compared with the result of PSO, MFO and other algorithms presented by Table 4. It is obviously notice that the fuel cost is reduced from 41679.5962 $/h and Lmax 0.2685 .

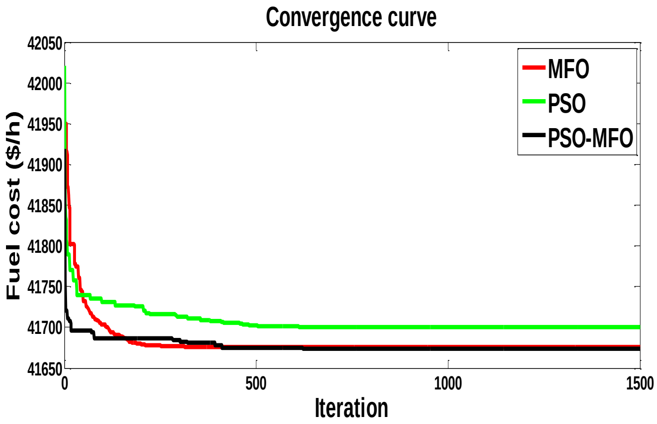

Fig. 4. Convergent curves of Case 4.

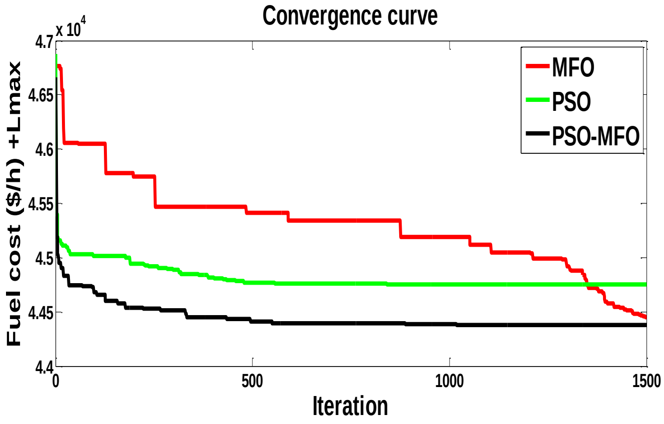

Fig. 5. Convergent curves of Case 5.

3. Conclusion

Hybrid Moth-Flame Optimizer and Particle Swarm Optimization technique are successfully applied to standard IEEE 30-bus and IEEE57-bus test systems to solve the optimal power flow problem with different cases study. The results give the optimal settings of control variables with various techniques which evidence the effectiveness of the different methods. It is clear from the statistical results of this technique is gives enhanced results than the other techniques .The results obtained from the PSO-MFO algorithm has good convergence characteristics and gives the better solutions compared to MFO and PSO methods which confirms the effectiveness of suggested method.

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	Case1			Case2			Case3		
Control variable	**PSO-MFO**	**MFO**	**PSO**	**PSO-MFO**	**MFO**	**PSO**	**PSO-MFO**	**MFO**	**PSO**
P_{G1} (MW)	177.1113	177.1178	178.1042	51.4869	51.4963	51.7855	177.3807	177.9249	177.8467
P_{G2} (MW)	48.6899	48.6915	49.1159	80	80	80	48.4400	49.4477	49.0647
P_{G5} (MW)	21.303	21.3039	21.3845	50	50	50	21.0604	22.0623	21.4496
P_{G8} (MW)	21.0241	21.0311	21.6787	35	35	35	20.9420	19.2722	22.1306
P_{G11} (MW)	11.8572	11.8567	10	30	30	30	11.8955	10.9907	10.0000
P_{G13} (MW)	12	12	12	40	40	40	12.3693	12.4625	12.0000
V_1(p.u)	1.1	1.1	1.1	1.06108	1.06041	1.01791	1.1000	1.1000	1.1000
V_2(p.u)	1.08768	1.08769	1.1	1.05702	1.05635	1.01273	1.0877	1.0900	1.1000
V_5(p.u)	1.06133	1.06131	1.07287	1.03784	1.0371	0.987273	1.0610	1.0618	1.1000
V_8(p.u)	1.06906	1.06911	1.07947	1.0444	1.04344	0.994135	1.0699	1.0716	1.1000
V_{11}(p.u)	1.1	1.1	1.1	1.07772	1.07236	1.1	1.0976	1.1000	1.1000
V_{13}(p.u)	1.1	1.1	1.1	1.04506	1.05278	1.1	1.0999	1.1000	1.1000
Qc_{10}(Mvar)	5	5	5	5	4.75306	0	4.6256	3.7122	0
Qc_{12}(Mvar)	5	5	5	4.99997	5	0	0.1204	1.5354	5.0000
Qc_{15}(Mvar)	5	5	5	5	4.9988	0.489859	3.2832	0.3476	5.0000
Qc_{17}(Mvar)	5	5	5	5	5	5	5.0000	4.5949	5.0000
Qc_{20}(Mvar)	5	0	0	3.83638	0	5	3.3958	1.2384	5.0000
Qc_{21}(Mvar)	5	5	5	4.99997	5	5	0.0037	0.4242	5.0000
Qc_{23}(Mvar)	2.60333	3.23431	5	2.76137	3.03971	0	4.8825	4.1577	0
Qc_{24}(Mvar)	5	5	5	5	5	5	4.2054	4.1909	0
Qc_{29}(Mvar)	2.29632	2.37528	5	2.06902	2.23597	0	0.0200	2.7961	0
T_{6-9}	1.04067	1.036	0.969235	1.1	1.07169	1.01272	0.9863	1.0038	1.1000
T_{6-10}	0.9	0.9	1.1	0.9	0.9	0.9	0.9244	0.9112	0.9000
T_{4-12}	0.977254	0.984169	1.1	0.984803	0.996874	1.02199	0.9806	0.9903	1.0032
T_{28-27}	0.960932	0.964347	1.01459	0.975691	0.975099	0.924266	0.9419	0.9518	0.9570
Fuel cost ($/h)	**798.9166**	**798.9706**	**799.7727**	967.6312	967.6536	968.3442	**799.2413**	**799.3654**	**800.6097**
VD	1.9733	1.8751	1.4034	0.8937	0.8873	0.6767	1.9108	1.8420	1.8938
$L_{\max}$	0.1261	0.1269	0.1336	0.1383	0.1382	0.1396	**0.1253**	**0.1255**	**0.1246**
Emission (ton/h)	0.3662	0.3662	0.3695	0.2072	0.2072	0.2073	0.3669	0.3687	0.3688
$p_{loss}(MW)$	8.5855	8.6010	8.8833	**3.0869**	**3.0963**	**3.3855**	8.6879	8.7604	9.0917

Case 1		**Case 2**		**Case 3**		
Algorithms	Fuel cost ($/h)	Algorithms	Ploss(MW)	Algorithms	Fuel cost ($/h)	Lmax
PSO-MFO	**798.9166**	PSO-MFO	**3.0869**	PSO-MFO	**799.2413**	**0.1253**
MFO	**798.9706**	MFO	**3.0963**	MFO	**799.3654**	**0.1255**
PSO	**799.7727**	PSO	**3.3855**	PSO	**800.6097**	**0.1246**
DE [16]	799.289	BHBO[4]	3.503	ICBO[7]	799.3277	0.1252
BHBO[4]	799.7727	DSA[8]	3.09450	DSA[8]	800.93316	0.124992
LTLBO[15]	799.4369	ABC[17]	3.1078	ABC[17]	801.6650	0.1379
DE[9]	799.0827	ARCBBO[18]	3.1009	ARCBBO[18]	805.4892	0.1383

Table 1. Optimal settings of the control variables for case1,2,3.

Table 2. Comparison of the results obtained for Case 1,2,3.

	Case4			Case5		
Control variable	PSO-MFO	MFO	PSO	PSO-MFO	MFO	PSO
PG1 (MW)	142.6714	147.7612	140.73009	140.4275	157.7242	136.2937
PG2 (MW)	84.7729	66.4101	100	94.93808	40.75784	100
PG3 (MW)	43.9613	46.0477	44.47088	44.45264	41.80069	40
PG6 (MW)	72.6891	76.6551	66.7949	62.04602	88.80556	56.86555
PG8 (MW)	457.7728	474.2835	458.4895	465.0457	504.1799	451.0707
PG9 (MW)	98.8645	85.9206	100	98.16951	45.93019	71.69979
PG12 (MW)	364.6985	368.6671	355.9957	360.9126	387.9271	410
V1(p.u)	1.0726	1.0615	1.062801	1.071895	1.06394	0.9954859
V2(p.u)	1.0753	1.0634	1.067189	1.075903	1.065135	1.000477
V3(p.u)	1.0629	1.0528	1.055248	1.061997	1.05774	0.9877916
V6(p.u)	1.0640	1.0594	1.064876	1.062172	1.060677	1.009988
V8(p.u)	1.0837	1.0756	1.081188	1.080282	1.0719	1.031486
V9(p.u)	1.0767	1.0647	1.067821	1.076625	1.065986	1.005678
V12(p.u)	1.0610	1.0482	1.046362	1.061625	1.053755	0.990594
Qc18(Mvar)	5.6097	4.5206	20	2.340649	1.875905	20
Qc25(Mvar)	11.8996	9.0239	10.80227	2.220668	5.218568	8.085422
Qc53(Mvar)	1.5312	14.9155	0	1.211505	16.26232	0
T4–18	0.9955	0.9084	1.1	1.021405	0.9499625	0.9
T4–18	1.0246	1.0363	1.097196	0.9614879	1.033199	1.1
T21–20	1.0083	0.9911	1.1	1.023278	1.016399	1.1
T24–25	0.9657	0.9015	1.1	0.9620894	0.9192871	0.9
T24–25	1.0773	1.0852	0.9	0.9391319	0.9933207	1.1
T24–26	1.0359	1.0194	1.061665	1.039977	0.9979963	1.047048
T7–29	0.9941	0.9964	1.025836	0.989397	0.9978153	0.9411672
T34–32	0.9120	0.9486	0.9730097	0.9003209	0.9	0.9
T11–41	0.9120	0.9204	0.9	0.9	0.9000075	1.1
T15–45	0.9889	0.9764	0.9857583	0.9912588	0.9815535	0.9
T14–46	0.9756	0.9675	0.9698113	0.9757561	0.966004	0.9
T10–51	0.9942	0.9792	0.9864258	0.996877	0.9884969	0.9222201
T13–49	0.9542	0.9423	0.9	0.9202492	0.910301	0.9
T11–43	1.0196	0.9808	1.019623	0.9906749	0.9942215	0.9
T40–56	1.0695	1.0127	1.1	1.036413	0.9404332	1.1
T39–57	0.9374	0.9601	1.1	1.022592	1.056499	0.9
T9–55	1.0179	1.0151	1.1	1.011227	1.031256	0.938692
Fuel cost ($/h)	**41674.1586**	**41676.3693**	**41700.55933**	**41679.5962**	**41838.983**	**41858.7842**
VD	1.7199	1.6015	1.90102	1.9115	1.7476	1.5288
$L_{\max}$	0.2750	0.2796	0.27970	**0.2685**	**0.27157**	**0.2809**
Emission (ton/h)	1.3527	1.4219	1.3399	1.3697	1.5995	1.41784
$p_{loss}(MW)$	14.6309	14.9454	15.6812	15.1923	16.3257	15.1297

Case 4		**Case 5**		
Algorithms	Fuel cost ($/h)	Algorithms	Fuel cost ($/h)	Lmax

Table 3. Optimal settings of the control variables for case 4 and 5.

PSO-MFO	**41674.1586**	PSO-MFO	**41679.5962**	**0.2685**
MFO	**41676.3693**	MFO	**41838.983**	**0.27157**
PSO	**41700.55933**	PSO	**41858.7842**	**0.2809**
TLBO [15]	41679.5451	MSA[19]	41675.9948	0.27481
DE[9]	41681.28	MDE[19]	41689.5878	0.27677
DSA[8]	41686.82	DSA[8]	41761.22	0.2383

Table 4. Comparison of the results obtained for Case 4 and 5.