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A new hybrid algorithm of particle swarm optimizer with grey wolves' optimizer for solving optimal power flow problem

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Abstract

The current trend of study is to hybridize two and more algorithms to gain the best solution in the area of optimization problems. In this paper presents the recently developed hybrid optimization technique named PSO-GWO combines the framework of particle swarm optimization (PSO) with grey wolves optimization (GWO) to solve the optimal power flow (OPF) problem. OPF is formulated as a nonlinear optimization problem with conflicting objectives and subjected to both equality and inequality constraints. The performance of this technique is deliberated and evaluated on the standard IEEE 30-bus test system with a single objective and multi-objective cases such as fuel cost minimization, Active power loss reduction, Voltage profile improvement and Voltage stability enhancement, and is compared to approaches available in the literature. The hybrid PSO-GWO provides better results compared to the original PSO, GWO, and other techniques mentioned in the literature as shown in the simulation results.

Keywords

Optimal power flow; Voltage stability; Active power loss; Emission; Constraints; Hybrid PSO-GWO.

Introduction

The Optimal Power Flow (OPF) is a significant appliance for planning and operation studies in the power system operator. OPF is a widely non-linear and non-convex optimization problem, and this is more difficulty in practical applications in the large number's presence of discrete variables. The goal of OPF is to provide the optimal settings of the power system by improving objective function while meeting the equality and inequality constraints [1], then this problem has been addressed by several researchers. The objective functions, such as the minimization of total fuel cost, improvement of voltage stability index and reduction of real power loss are considered individually in the literature for this study.

The problem of power flow is one of the fundamental problems in which the load and the powers of the generator are given or corrected. The OPF has a long history in its development, and it was primarily introduced by Carpentier in 1962, and the next investigations on OPF in [2]. However, it took a long time to turn into an effective technique that could be applied in daily use. The actual interest for OPF is focused on its capability to solve for the optimal solution that has considered the security of the system. The optimal power flow has been applied to regulate the active power outputs and voltages of the generator, transformer tap settings, shunt reactors/capacitors and other controllable variables to minimize the generator fuel cost, network active power loss, voltage stability index, while keeping all the load bus voltages, generator reactive power outputs, network power flows, and all other state variables in the power system within their secure and operational bounds. In its most common problem formulation, the OPF is a non-convex, static, large-scale optimization problem with both continuous and discrete control variables [3]. Even in the absence of non-convex generator operating cost functions, prohibited operating zones (POZs) of generating units, and discrete control variables, the OPF problem is a non-convex because of the existence of the non-linear alternating current power flow equality constraints. The existence of discrete control variables, such as transformer tap positions, switchable shunt devices, phase shifters, further complicates the formulation and solution of the problem.

Different conventional optimization methods have been used to solve the OPF problem. These involve Newton methods [4], linear programming [5], and quadratic programming [6]. A comprehensive survey of different conventional optimization techniques used to solve OPF problems was presented. Nevertheless, in practice, conventional techniques suffer from some weakness. Some of its shortcomings through other things are: First, they do not assure to find the global optimum, second, conventional techniques involve complex computations with a long time, and they do not suitable for discrete variables [7].

During the last little decades, a lot of powerful meta-heuristics were developed. Several of them have been implemented to the OPF problem with very successfully. various of the modern implementations of meta-heuristics for the OPF problem are: Black Hole (BH) [8], League Championship Algorithm (LCA) [9], Gravitational Search Algorithm (GSA)[10], Artificial Bee Colony (ABC)[11], Group Search Optimization (GSO)[12], Imperialist Competitive Algorithm (ICA) [13], Differential Search Algorithm (DSA) [14], Teaching Learning Based Optimization (TLBO)[15], and Krill Herd Algorithm (KHA) [16], adaptive clonal selection algorithm(ACSA) [17] .Though, because of changing objectives while solving OPF problems, no algorithm is the greatest one to solve all the OPF problems. Consequently, there is still a need for a novel algorithm, which can effectively solve the most of OPF problems.

Particle Swarm Optimization (PSO) has an uncomplicated concept, simple to carry out, Relative effectiveness to control parameters and computational adequacy[18] Although it has many advantages, it obtain restricted in the local minimum, When dealing with severely constrained problems because of limited local/global search abilities [19, 20]. Gray Wolf Optimizer (GWO) is a powerful evolutionary algorithm newly developed by Mirjalili [20] it has the capability to converge to the superior quality near-optimal solution and has preferable convergence properties than other dominant techniques. In addition, GWO has a perfect balance between exploration and exploitation that result in avoidance high of the local optima.

In this article, we introduce a new hybrid algorithm, named a PSO-GWO which is constructed on incorporating PSO with GWO algorithms. The effectiveness of this technique to the OPF problem with non-smooth cost functions like as fuel cost with prohibited zones, piecewise quadratic cost function, fuel cost with valve-point effects is tested and analyzed on the standard IEEE 30-bus test systems With various objective functions and is Compared to the techniques mentioned in the literature. Investigational results on the OPF problem show that the modern hybrid algorithm has preferable effectiveness in both convergence and global excellent, compared with original PSO, GWO and other algorithms mentioned in the literature. We confirm that the suggested method has perfect efficiency and capability to get a solution of OPF problem. This suggested technique can optimize the number of various objectives and can be useful for system operators in choosing a wise decision in implementing the system performance.

Material and method

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 takes into account the operating limits of the system and it can be mathematically formulated as a nonlinear constrained optimization problem as follows, Eq. (1):

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

$g(x,u) \leq 0$

Subject to: $h(x,u) = 0$

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; the control variables u and the state variables x of the OPF problem are explained in (2) and (3), respectively.

Control variables:

These are the set of variables that can be regulated to satisfy the load flow equations [21]. The set of control variables in the mathematical formulation of the OPF problem are:

PG: is the i-th active power bus generator (except swing generator).

VG: is the voltage magnitude at i-th PV bus (generator bus).

T: is the transformer tap setting.

QC: is the shunt VAR compensation.

The control variables ***U*** can be formulated as Eq. (2):

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

Where: *NC*, *NT* and *NG* are the number of *VAR* compensator, the number of regulating transformers and the number of generators respectively.

State variables:

These are the set of variables that report any unique state of the system [21]. The set of state variables for mathematically formulated the OPF problem as follow:

PG1: is the generator active power at slack (or swing) bus.

VL: is the bus voltage of *p-th* load bus (PQ bus).

QG: reactive power generation of all generator units.

SL: transmission line loading (or line flow)

The state variables ***X*** can be formulated as Eq. (3):

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

Where: *NL*, and *nl* are the number of load buses and the number of transmission lines, respectively.

Constraints:

The OPF constraints can be classified into equality and inequality constraints, as explained in the next sections.

1. **Equality constraints**

The equality constraints that express the typical nonlinear power flow equations that control the power system, presented as follows.

a) Real power constraints, Eq. (4):

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

b) Reactive power constraints, Eq. (5):

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

Where: NB is the number of buses, P_D and Q_D are active and reactive load demands, respectively, $\delta_{ij} = \delta_i - \delta_j$ is the difference in voltage angles between bus *i* and bus *j* G_{ij} is the transfer conductance and B_{ij} is the susceptance between bus *i* and bus *j*, respectively.

2. **Inequality constraints:**

The Inequality constraints that reflect operational of the system and the system's physical limits presented as follows.

1. Generator constraints. For all generators comprising the slack: voltage, active and reactive outputs shall be limited by their minimum and maximum limits as follows, Eq. (6-8):

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \forall i \in NG \tag{6}$$

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

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

2. *Transformer constraints.* Transformer tap settings must be limited to their specified minimum and maximum limits as follows, Eq. (9):

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

Shunt VAR compensator constraints. Shunt VAR compensator have to be limited by their lower and upper limits as follows, Eq. (10):

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

Security constraints:

These comprise the constraints of voltage magnitude at load buses and transmission line loadings. The Voltage of each load bus has to be limited within its minimum and maximum operating limits. Line flow through each transmission line must be limited by its capacity limits. These constraints can be expressed as given follows, Eq. (11-12):

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

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

Where: $V_{L_p}^{\min}$ and $V_{L_p}^{\max}$ - represents lowest and the upper load voltage of *i-th* unit, S_{l_q} - represents apparent power flow of *i-th* branch $S_{l_q}^{\max}$ - represents maximum apparent power flow limit of i-th branch.

Particle swarm optimization (PSO):

Particle swarm optimization, inspired by societal the conduct of birds is an optimization technique based on swarm intelligence that suggested a population-based research process by taking particles and moving them around in the search space for be given the best solution for the problem. In PSO, particles change position in a multi-dimensional search space, any particle adjusts its location pursuant to its own experiment and the experiment of neighbouring particles, and take advantage of the best position encountered by itself and its neighbours. The direction of the swarm of a particle is determined by all the neighbouring particles of the particle and experiment of its history [22]. PSO is a non-deterministic, stochastic optimization method and supplies a population-based search operation for global optimization, Have the main advantage of easy to achieve and few parameters to regulate. PSO involves two expressions A and B. Position and speed are updated over the course of iteration from these follows Eq. (13-15):

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

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

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

Where: 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].

Grey wolf optimization (GWO)

Mirjalili et al are the first to propose a new algorithm called are Grey Wolf Optimization [23], The technique was inspired by the popular conduct and hunting mechanism of grey wolves in nature. In a group, the grey wolves follow so strong social leadership hierarchy. The group leaders are male and female, named alpha (α). The second level of grey wolves, which are subaltern wolves that assist leaders, are named beta (β). The deltas (δ) are the grey wolves' third level that must submit to alphas and betas but controls the omega. The downgrade of the grey wolf is omega (ω), which must capitulate to all other wolves that govern. The GWO technique is presented in mathematical models as next [24].

Social hierarchy

In the mathematical pattern of the social hierarchy of grey wolves, alpha (α) is considered the most suitable solution. As a result, the second preferable solution is called beta (β) and the third preferable solution is called delta (δ) respectively. The remaining candidate solutions are taken as omega (ω). In the GWO, the optimal (shooting) alpha, beta, and delta are guided. The omega wolves must come behind these wolves [24].

Encircling prey

The grey wolves surround victim through the hunt. The encircling conduct can be modelled mathematically as follows, Eq. (16-17):

$$\vec{M} = \left|\vec{N} * \vec{X}(t) - \vec{X}(t)\right| \quad (16)$$

$$\vec{X}(t+1) = \vec{X}_r(t) - \vec{L} * \vec{M} \quad (17)$$

Where: t - shows the existing iteration, $\vec{L}$ and $\vec{N}$ are coefficient vectors, $\vec{X}_r$ is the position vector of the victim and $\vec{x}$ shows the position vector of a grey wolf. The vectors $\vec{L}$ and $\vec{N}$ are calculated as follows, Eq. (18-19):

$$\vec{L} = 2\vec{l} * \vec{r}_1 - \vec{l} \quad (18)$$

$$\vec{N} = 2 * \vec{r}_2 \quad (19)$$

Where: elements of 'l' are linearly diminished from 2 to 0 through the course of iterations and r1, r2 are arbitrary vectors in the cavity [0,1].

Hunting

Hunting is generally guided by alpha, beta and delta, which have a better understanding of the potential location of the victim. The other search agents have to update their positions based on the preferable search position of agent. The position of their agent update can be expressed as follows Eq. (20-22) [25]:

$$\begin{aligned} \vec{M}_\alpha &= \left|\vec{N}_1 \cdot \vec{X}_\alpha - \vec{X}_\alpha\right| \\ \vec{M}_\beta &= \left|\vec{N}_1 \cdot \vec{X}_\beta - \vec{X}_\beta\right| \\ \vec{M}_\delta &= \left|\vec{N}_1 \cdot \vec{X}_\delta - \vec{X}_\delta\right| \end{aligned} \quad (20)$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{L}_1 \cdot \left(\vec{M}_\alpha\right) \\ \vec{X}_2 &= \vec{X}_\beta - \vec{L}_1 \cdot \left(\vec{M}_\beta\right) \\ \vec{X}_3 &= \vec{X}_\delta - \vec{L}_1 \cdot \left(\vec{M}_\delta\right) \end{aligned} \quad (21)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (22)$$

Search for prey and attacking prey

The 'L' is an arbitrary value in the interval [-2a, 2a].When | L | <1, the wolves are forced to offensive the victim. Offensive the victim is the exploitation capability and searching for a victim is the exploration capability. The random values of 'L' are employed to force the search agent to move far from the victim. When | L | > 1, grey wolves are forced to move far from the victim.

Hybrid PSO-GWO

Whoever the technique is used for optimization, it has advantages and disadvantages. Exams were suggested for enhancement to achieve the best possible technique. Hybridization techniques can help to find enhancement in order to the advantages and disadvantages of each technique are compensated. Presently, the hybrid meta-heuristics have become more deliberative in order to the best results for some optimization problems have been received with hybrid methods. In this article, we have select two new meta-heuristics (PSO and GWO) to solve the OPF problem, but like all techniques, PSO and GWO have advantages and disadvantages. So as to combine the characteristics of the two techniques to draw their benefits and have the preferable results, we hybridized them as appear in Figure 1.

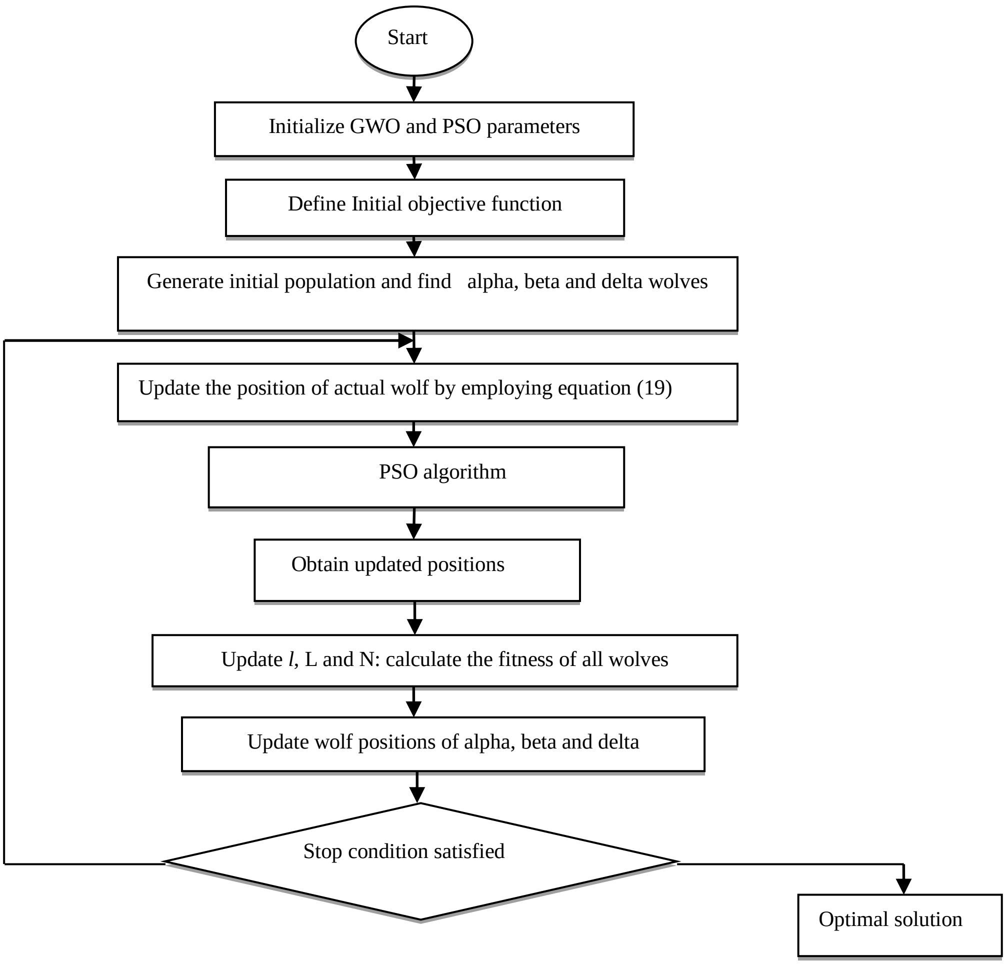

Figure 1. Flowchart of the hybrid GWO-PSO algorithm

The PSO-GWO algorithm has been using to solve the OPF problem for exam system and for many cases with various objective functions. The considered power systems networks are the IEEE 30-bus test system network. The advanced software program is written in MATLAB computing environment and used on a 2.20 GHz i7 personal computer. In our study, the PSO-GWO population size or a number of stars is selection to be 50.

IEEE 30-bus test system

In order to illustrate the performance of the proposed PSO-GWO method, it has been examined first on the standard IEEE 30-bus test system. The standard IEEE 30-bus system selection in this paper has the next characteristics [26]: 6-generators at buses 1, 2, 5, 8, 11 and 13, 4-transformers with off-nominal tap ratio at lines 11, 12, 15 and 36, 9-shunt VAR compensation buses at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29.

In addition, line data, bus data, generator data, and lower and upper restriction for control variables are presented in [27].

For this exam system, Six various cases have been studied with various objectives and all the obtained results are outlined in Tables 1, 4 and 7. The first column of this table appears the optimal control settings found here:

- PG1Through PG6 and VG1 through VG6 represent the powers and the voltages of generator 1 through generator 6.
- *T11, T12, T15 and T36* are the tap settings of transforms involved between lines 11, 12, 15 and 36.
- *QC10, QC12, QC15, QC17, QC20, QC21, QC23, QC24 and QC29* represent the shunt VAR compensations connected to buses 10, 12,15, 17, 20, 21, 23, 24 and 29.

Moreover, fuel cost *($/h)*, active power losses *(MW)*, voltage deviation and $L_{\max}$ represent the total fuel cost of the system, the total active transmission losses, the deviation of load voltages from 1and the index of stability, respectively. More description of these results will be presented in the next sections.

Case 1: Minimization of generation fuel cost

The first case studied in this article is the basic case of minimizing the cost generation fuel expressed by a quadratic function. Therefore, the objective function of this case is Eq. (23):

$$J = \sum_{i=1}^{NG} f_i \left(\$/h\right) \tag{23}$$

Where: *fi* - is the fuel cost of the *ith* generator. Usually, the OPF generation fuel cost curve is formulated by a quadratic function.

Hence, *fi* can be formulated as follows Eq. (24):

$$f_i = \left(a_i + b_i P_{G_i} + c_i P_{G_i}^2\right) \tag{24}$$

Where: a_i, b_i, c_i - are the element, the linear and the quadratic cost coefficients of the *ith* generator, respectively. The values of these coefficients are presented in [27].

Figure 2 appears the trend of total fuel cost over iterations. It seems that the proposed technique has good convergence characteristics. The optimal settings of control variables are presented in Table 1. The total fuel cost obtained by the suggested PSO-GWO technique is (799.1079 $/h). Compared to the original PSO, GWO the total fuel cost is significantly decreased.

Using the identical conditions (limits of control variables, initial conditions, and system data), the results obtained in Case 1 apply the PSO-GWO technique are compared to other methods described in the literature as appears in Table 2. There is some proof, that the suggested technique outperforms several methods used to solve the OPF problem by decreasing of generation fuel cost. For instance, the results obtained by the PSO-GWO are better than the ones obtained the GWO and PSO methods.

Case 2: Minimization of fuel cost and voltage deviation

Bus voltage is one of the most significant and considerable security and service quality indices [27]. Reducing only the total cost in the OPF problem as in Case 1 may result in a suitable Solution, but voltage profile may not be reasonable. Consequently, this case purposes at minimizing fuel cost with a improve voltage profile by considering a dual objective function.

The voltage profile is optimized by reducing the load bus voltage deviation (VD) from 1.0 p.u, the objective function, in this case, can be formulated as follows Eq. (25):

$$J = J_{\text{cost}} + wJ_{voltageDeviation} \tag{25}$$

Where: w - is an appropriate weighting factor, to be chosen by the user to accord a weight to each of the two expressions of the objective function. In this case, *w* is selection as 100.

J_{cost} and $J_{VoltageDeviation}$ are presented as follows Eq. (26-27):

$$J_{\cost} = \sum_{i=1}^{NG} f_i \tag{26}$$

$$J_{voltageDeviation} = \sum_{k=1}^{NL} |V_i - 1| \tag{27}$$

Results and discussion

The PSO-GWO technique has been utilized to search for the optimal solution of the problem. The variations in the fuel cost and voltage deviation through the iterations are outlined in Figure 3a and Figure 3b.

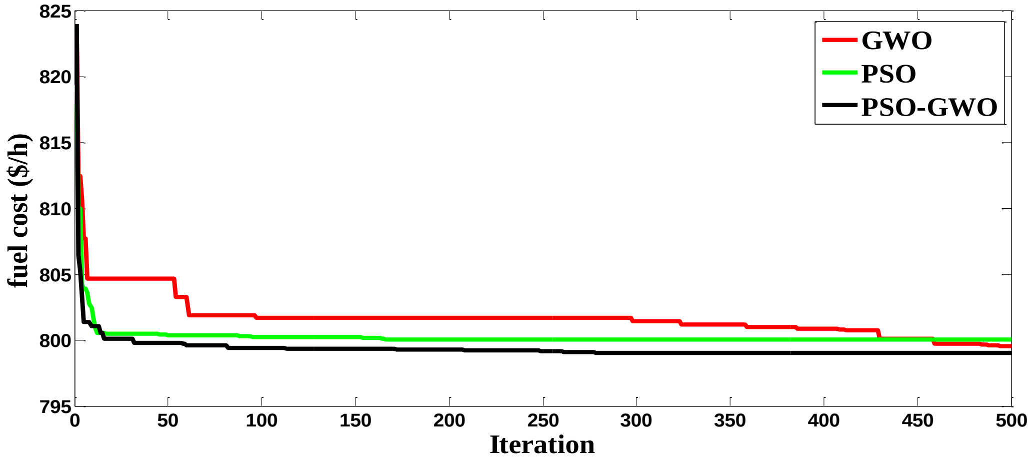

Figure 2. Convergent curves of Case 1

The optimal settings of the control variables are presented in Table 1. Apply PSO-GWO the fuel cost and the voltage deviation yielded are (**803.5881**$/h) and (**0.1044** p.u.), respectively. The voltage profile obtained by PSO-GWO is compared with other algorithms as appears in Table 2. It is clear that the voltage profile is the least among all other comparable methods. It is decreased from **1.6899** p.u. in the case 1 to **0.1044** p.u. in case 2, Hence, in case 2, the fuel cost is slightly augmented by 0.55% compared to case 1.

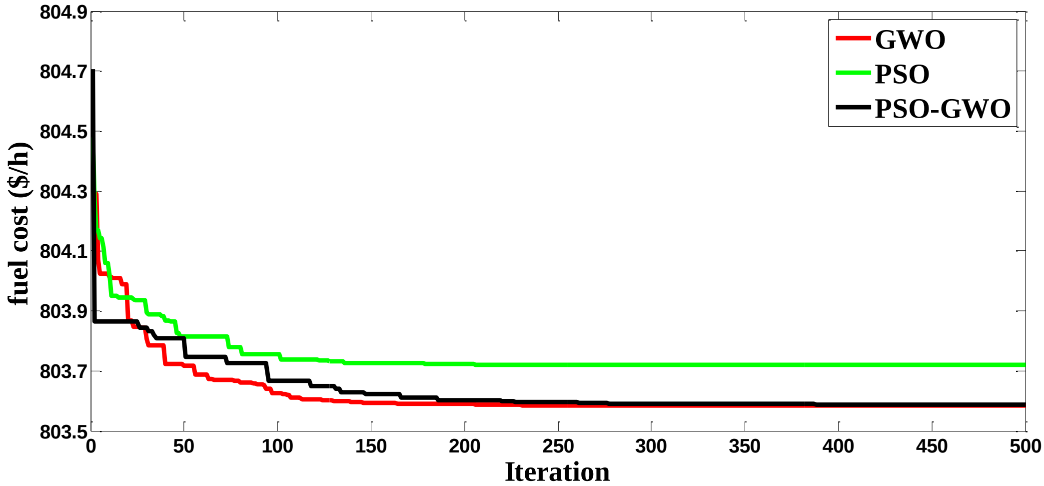

Figure 3a. Convergent curves of Case 2

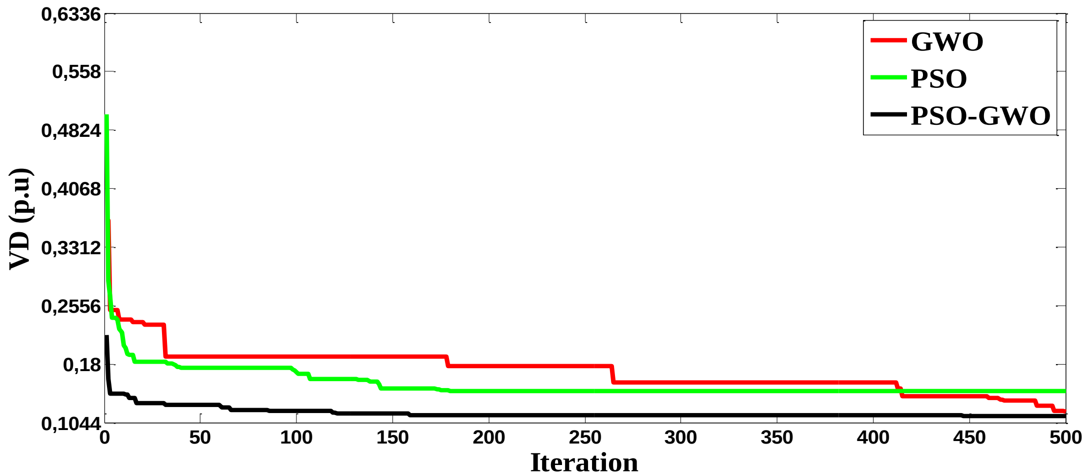

Figure 3b. Convergent curves of Case 2

CASE 3: Minimization of fuel cost considering valve point effect

So as to have a realistic and greater effective modeling of generator cost functions, the valve point–effect must be considered. The generating units with multi-valve steam turbines display a major variation in the fuel-cost functions and output a ripple-like effect [30]. So as to considered the valve-point effect of generating units, a modeled as a sinusoidal term is added to the cost function. Thus, the objective function can be formulated as follow Table 1 and Table 2:

Table 1. Optimal settings of the control variables for case1 to case 3.

Control variable	Case 1			Case 2			Case 3		
	PSO-GWO	GWO	PSO	PSO-GWO	GWO	PSO	PSO-GWO	GWO	PSO
P_{G1} (MW)	176.57	176.66	177.84	177.52	176.09	178.16	200.17	200.08	200.00
P_{G2} (MW)	48.81	47.83	49.06	49.26	48.92	49.11	43.14	41.86	43.53
P_{G5} (MW)	21.61	21.19	21.48	21.77	21.59	21.64	18.32	18.49	18.63
P_{G8} (MW)	21.02	20.25	22.09	22.74	22.39	22.44	10.08	11.28	10.00
P_{G11} (MW)	11.78	12.91	10	10	12.21	10.04	10.00	10.01	10.00
P_{G13} (MW)	12.21	13.21	12	12	12	12	12.00	12.01	12.00
V_1(p.u)	1.1	1.1	1.1	1.05	1.04	1.06	1.10	1.10	1.10
V_2(p.u)	1.09	1.09	1.1	1.03	1.02	1.04	1.08	1.09	1.10
V_5(p.u)	1.06	1.06	1.1	1.01	1.01	1.01	1.06	1.06	1.08
V_8(p.u)	1.07	1.07	1.1	1.00	1.01	1.00	1.06	1.07	1.10
V_{11}(p.u)	1.1	1.1	1.1	1.1	0.98	1.1	1.10	1.09	1.10
V_{13}(p.u)	1.1	1.1	1.1	0.97	1.03	0.96	1.10	1.10	1.10
Qc_{10}(Mvar)	1.80	0.38	0	0	0	0	5.00	0.18	0
Qc_{12}(Mvar)	2	0.12	0	1.35	2.24e-06	5	0.25	0.23	5.00
Qc_{15}(Mvar)	5	1.57	0	5	5	5	3.92	0.12	5.00
Qc_{17}(Mvar)	5	0.09	0	0	5	5	3.53	0.22	0
Qc_{20}(Mvar)	0.01	2.47	5	5	5	5	0.59	3.43	0
Qc_{21}(Mvar)	4.87	1.49	5	5	5	5	5.00	2.68	5.00
Qc_{23}(Mvar)	3.08	1.58	5	5	5	5	0.02	0.07	3.66
Qc_{24}(Mvar)	5	1.79	5	4.93	5	5	5.00	1.49	5.00
Qc_{29}(Mvar)	0.46	3.22	0	2.64	5	5	3.81	1.61	5.00
$T_{6–9}$	1.04	1.04	1.1	1.1	0.99	0.96	1.02	1.08	0.99
$T_{6–10}$	0.90	0.92	0.9	0.9	0.9	1.1	0.93	0.93	1.10
$T_{4–12}$	1.07	1.02	1.02	0.92	1.02	0.9	1.01	1.06	1.10
$T_{28–27}$	0.96	0.99	0.99	0.97	0.98	0.98	0.99	0.99	1.10
Fuel cost ($/h)	**799.1079**	**799.5063**	**800.4361**	**803.5881**	**803.5802**	**803.7326**	**829.8394**	**830.4784**	**831.6223**
VD	1.6899	1.3010	1.6857	**0.1044**	**0.1151**	**0.1464**	1.5136	0.9963	1.0404
$L_{\max}$	0.1283	0.1338	0.1294	0.1487	0.1491	0.1490	0.1321	0.1362	0.1453
Emission (ton/h)	0.3646	0.3642	0.3687	0.3677	0.3631	0.3695	0.4433	0.4426	0.4425
$p_{loss}(MW)$	8.5944	8.6613	9.0431	9.8890	9.8007	9.9780	10.3089	10.3455	10.7552

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

Case 1		Case 2		Case 3	
Algorithms	Fuel cost ($/h)	Algorithms	VD (pu)	Algorithms	Fuel cost ($/h)
PSO-GWO	**799.1079**	PSO-GWO	**0.1044**	PSO-GWO	**829.8394**
GWO	**799.5063**	GWO	**0.1151**	GWO	**830.4784**
PSO	**800.4361**	PSO	**0.1464**	PSO	**831.6223**
MGBICA [31]	801.1409	BHBO [8]	0.1262	ICBO[36]	830.4531
ABC [32]	800.660	DE [34]	0.1357	BSA[21]	830.7779
HSFLA-SA[33]	801.79	IEM [35]	0.1270		

$$f(x,u)=\sum_{i=1}^{NG}\left(a_i+b_iP_{G_i}+c_iP_{G_i}^2\right)+\left|d_i\times\sin\left(e_i\times\left(P_{G_i}^{\min}-P_{G_i}\right)\right)\right| \tag{28}$$

Where: d_i and e_i are the coefficients that show the valve-point loading effect.

In this case to arrive at a rise in cost than in case 1 with a conclusive value being **829.8394**$/h, obtained by PSO-GWO. The optimal control variables obtained are shown in Table 1 output outcome of a method used in our study are better than most of the results revealed in past literature on the problem of OPF that is presented in table 2.

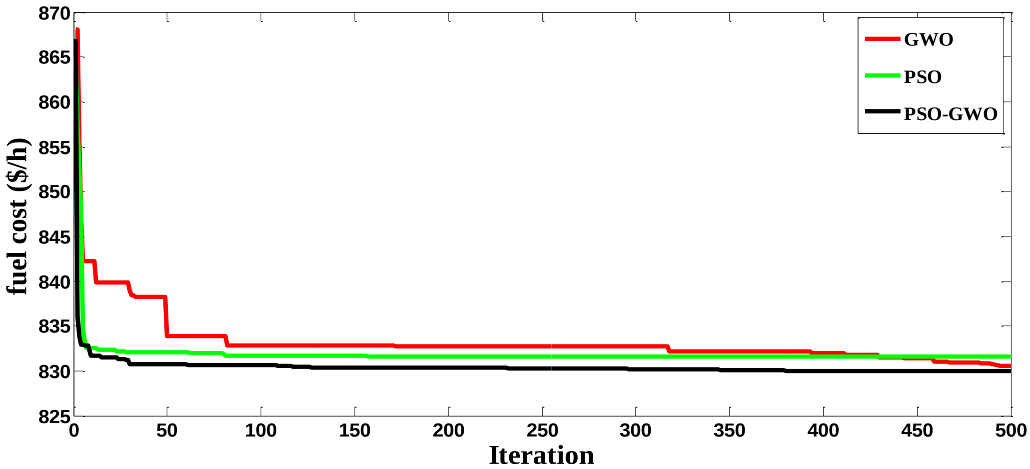

Figure 4. Convergent curves of Case 3

Case 4: Minimization of fuel cost and enhancement of voltage stability

The prediction of voltage instability is a problem of paramount significance in power systems. In [28] Kessel and Glavitch have developed a voltage stability index named $L_{\max}$ which is defined build on local indicators L_j and it is presented by Eq. (29):

$$L_{\max} = \max\left(L_j\right), \qquad j = 1,2,\ldots,NL \tag{29}$$

Where: L_j is the local indicator of bus j and it is given as follows Eq. (30)

$$L_j = \left|1 - \sum_{i=1}^{NG} H_{LG_{ji}} \frac{V_i}{V_j}\right| \qquad j = 1,2,\ldots,NL \tag{30}$$

Where: H - matrix is produced by the partial inversion of Y_{bus}. More specifics can be given in [28].

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 $L_{\max}$ the complete system [29]. Hence, the objective function can be formulated as Eq. (31):

$$J(x,u) = \left(\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2\right) + \lambda_{L_{\max}}\left(L_{\max}\right) \tag{31}$$

Where: $\lambda_{L_{\max}}$ is a weighting factor chosen as 100 in this work. The results of the optimization study are presented in Table 3 while the direction of convergence appears in Figure 5a and 5b. It seems that the L_{max} has been decreased from **0.1283** to **0.1251**compared with CASE 1,

Hence the results obtained are compared with other algorithms as given in Table 4.

Table 3. Optimal settings of the control variables for case 4 to case 6.

Control variable	Case 4			Case 5			Case 6		
	PSO-GWO	GWO	PSO	PSO-GWO	GWO	PSO	PSO-GWO	GWO	PSO
P_{G1} (MW)	177.13	178.06	177.9656	113.11	112.85	111.84	51.39	51.55	51.37
P_{G2} (MW)	49.22	49.64	49.1534	59.11	58.98	58.40	79.93	79.91	80.00
P_{G5} (MW)	21.99	21.99	21.3946	27.48	27.61	27.35	50.00	49.96	50.00
P_{G8} (MW)	18.60	19.01	21.9131	35.00	35.00	35.00	35.00	34.94	35.00
P_{G11} (MW)	12.28	11.51	10.0000	26.60	27.87	30.00	29.99	30.00	30.00
P_{G13} (MW)	12.98	12.14	12.0000	27.19	26.29	26.05	40.00	39.95	40.00
V_1(p.u)	1.10	1.10	1.1000	1.10	1.10	1.10	1.10	1.10	1.10
V_2(p.u)	1.09	1.09	1.1000	1.09	1.09	1.10	1.10	1.10	1.10
V_5(p.u)	1.07	1.07	1.0744	1.07	1.07	1.08	1.08	1.08	1.10
V_8(p.u)	1.07	1.08	1.0852	1.08	1.08	1.10	1.09	1.09	1.10
V_{11}(p.u)	1.10	1.10	1.0624	1.10	1.10	1.10	1.10	1.10	1.10
V_{13}(p.u)	1.10	1.10	1.1000	1.10	1.10	1.10	1.10	1.10	1.10
Qc_{10}(Mvar)	5.00	1.81	0	2.89	2.24	5.00	0.01	3.44	5.00
Qc_{12}(Mvar)	0.05	0.30	5.0000	0.96	3.62	0	0.47	0.85	5.00
Qc_{15}(Mvar)	3.04	0.39	0	5.00	1.22	0	2.71	2.78	5.00
Qc_{17}(Mvar)	0.02	1.73	5.0000	4.72	0.53	5.00	4.58	3.83	0
Qc_{20}(Mbar)	5.00	0.10	5.0000	3.91	0.00	0	5.00	1.07	0
Qc_{21}(Mvar)	0.36	4.87	0	0.27	1.33	5.00	0.50	3.70	5.00
Qc_{23}(Mvar)	0.51	0.17	5.0000	1.82	1.74	0	4.27	3.86	0
Qc_{24}(Mvar)	0.62	0.55	5.0000	5.00	0.03	0	5.00	1.02	5.00
Qc_{29}(Mvar)	0.84	0.24	0	1.14	0.02	2.21	0.03	1.80	2.21
T_{6-9}	0.99	0.98	0.9000	1.04	0.97	0.97	1.04	1.08	1.10
T_{6-10}	0.91	0.93	1.1000	0.92	1.02	1.10	0.92	0.90	0.90
T_{4-12}	0.99	0.98	1.0132	1.01	1.03	1.10	1.01	1.00	1.01
T_{28-27}	0.94	0.94	0.9426	0.99	0.98	1.01	0.97	0.99	0.99
Fuel cost ($/h)	**799.7188**	**799.9043**	**800.3247**	**834.9486**	**835.9200**	**838.1687**	966.9805	966.5853	967.3598
VD	1.8169	1.7976	1.7615	1.6909	1.3259	1.2613	1.8087	1.6767	1.8015
$L_{\max}$	**0.1251**	**0.1250**	**0.1255**	0.1303	0.1327	0.1343	0.1281	0.1302	0.1282
Emission (ton/h)	0.3659	0.3690	0.3692	**0.2426**	**0.2422**	**0.2406**	0.2072	0.2072	0.2072
$p_{loss}(MW)$	8.7897	8.9339	9.0267	5.0851	5.1929	5.2424	**2.8946**	**2.9100**	**2.9732**

Table 4. Comparison of the results obtained for Case 4 to Case 6.

Case 4		Case 5		Case 6	
Algorithms	$L_{\max}$	Algorithms	Emission(ton/h)	Algorithms	Ploss (MW)
PSO-GWO	**0.1251**	PSO-GWO	**0.2426**	PSO-GWO	**2.8946**
GWO	**0.1250**	GWO	**0.2422**	GWO	**2.9100**
PSO	**0.1255**	PSO	**0.2406**	PSO	**2.9732**
ABC [32]	0.1379	MOGWO [40]	0.245126	MSA[39]	3.1005

ARCBBO[37]	0.1369	NSGA-II[40]	0.3214	ABC[32]	3.1078
Gbest-ABC [38]	0.1370			ARCBBO[37]	3.1009

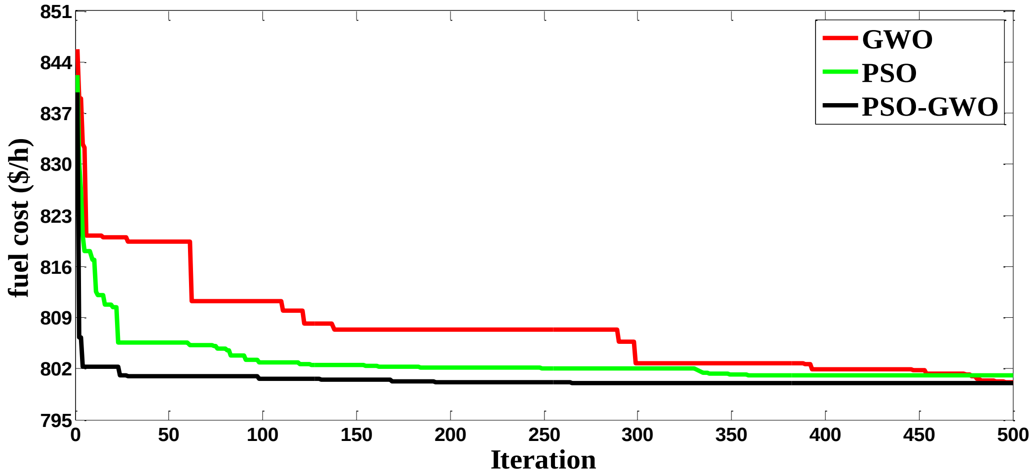

Figure 5a. Convergent curves of Case 4

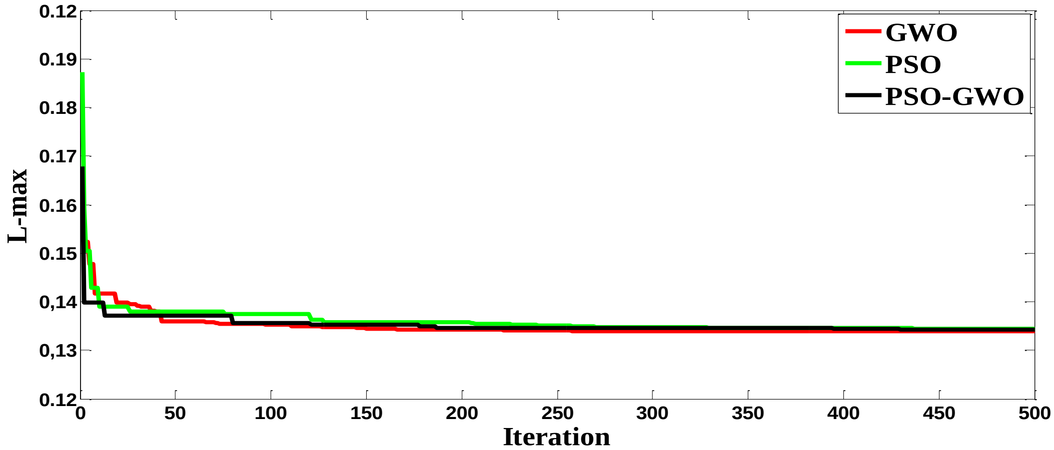

Figure 5b. Convergent curves of Case 4

CASE 5: Minimization of fuel cost and emission

Electrical power generation from conventional sources of energy emits hazardous gases into the environment. The quantity of sulfur oxides (SOx), nitrogen oxides (NOx) emission in tons per hr (t/h) is higher with the rise in generated power (in p.u. MW) next to the relationship presented in Eq. (32).

$$f\left(x,u\right)=emission=\sum_{i=1}^{NG}\left[\left(\alpha_i+\beta_i P_{G_i}+\gamma_i P_{G_i}^2\right)\times 0.01+\omega_i e^{\left(\mu_i P_{G_i}\right)}\right] \qquad (32)$$

Where: α_i, β_i, Υ_i, ω_i and μ_i are all emission coefficients provided in [21]. The objective function for this case is assumed by Eq. (33):

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG}a_i+b_i P_{G_i}+c_i P_{G_i}^2\right)+\lambda_E\times emission \qquad (33)$$

The weight factors are selected as λ_E = 100 in this case.

The results yielded after optimization applied the PSO-GWO technique are presented in Table 3 and the trend of optimization is shown in Figure 6. The results appear that the emission has been decreased from (**0.3646** ton/h) to (**0.2426** ton/h), Thus, the total fuel cost has augmented from (**799.1079**$/h) to (**834.9486**$/h) i.e. by 4.29% compared with CASE 1, and the results obtained are compared with other techniques as shown in Table 4.

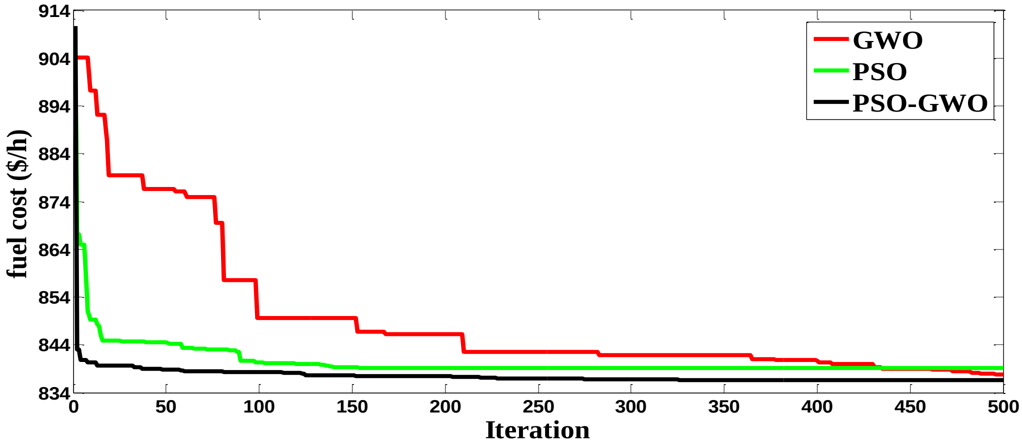

Figure 6. Convergent curves of Case 5

Case 6: Minimization of real power loss

In this case, the purpose of the OPF problem is to minimize power losses; the real power loss to be minimized is formulated as follows, Eq. (34):

$$f\left(x,u\right)=P_{loss}=\sum_{i=1}^{nl}\sum_{j=1,j\neq i}^{nl}G_{ij}\left[V_i^{\,2}+V_j^{\,2}-2V_iV_j\cos\left(\delta_{ij}\right)\right] \quad (34)$$

Where: $\delta_{ij}=\delta_i-\delta_j$ is the difference in voltage angles between bus *i* and bus *j* and G_{ij} is transfer conductance.

The tendency to decrease the objective function of total real power transmission loss using the PSO-GWO technique appears Figure 7. The optimal settings of the control variables are presented in Table 3 in this case 6 by PSO-GWO result in real power losses of 2.8946 MW, better than all the results summarized in Table 4.

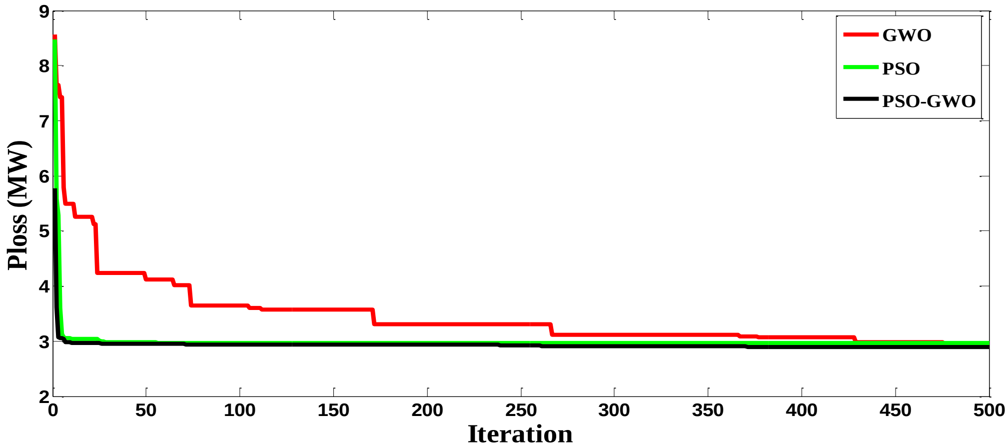

Figure 7. Convergent curves of Case 6

Conclusions

In this article, a new Hybrid technique called PSO-GWO is applied to solve OPF problems. One test system and six cases have been studied in order to evaluate the performance of the suggested technique. The OPF problem was reported as a non-linear optimization problem with equality and inequality constraints. Where several objective functions have been considered to minimize the fuel cost, to improve the voltage profile, and to enhance the voltage stability. However, the yielded results have been compared to those yielded using standard optimization techniques such as PSO, GWO. The essential conclusion that can be extracted from this article is that the PSO-GWO is a very efficient and robust technique for solving OPF problems. It has perfect convergence characteristics and can be realized better effectiveness than some well-known optimization techniques. A comparison of the results yielded from PSO-GWO and other techniques confirm the superiority of the algorithm for the suggested PSO-GWO on stochastic methods in terms of solution efficiency for the OPF problems.

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