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Multi-Mean Scout Particle Swarm Optimization (MMSCPSO) based Reactive Power Optimization in Large-Scale Power Systems

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The particle swarm optimization (PSO) is a population-based algorithm belonging into metaheuristic algorithms and it has been used since many decades for handling and solving various optimization problems. However, it suffers from premature convergence and it can easily be trapped into local optimum. Therefore, this study presents a new algorithm called multi-mean scout particle swarm optimization (MMSCPSO) which solves reactive power optimization problem in a practical power system. The main objective is to minimize the active power losses in transmission line while satisfying various constraints. Control variables to be adjusted are voltage at all generator buses, transformer tap position and shunt capacitor. The standard PSO has a better exploitation ability but it has a very poor exploration ability. Consequently, to maintain the balance between these two abilities during the search process by helping particles to escape from the local optimum trap, modifications were made where initial population was produced by tent and logistic maps and it was subdividing it into sub-swarms to ensure good distribution of particles

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within the search space. Beside this, the idle particles (particles unable to improve their personal best) were replaced by insertion of a scout phase inspired from the artificial bee colony in the standard PSO. This algorithm has been applied and tested on IEEE 118-bus system and it has shown a strong performance in terms of active power loss minimization and voltage profile improvement compared to the original PSO Algorithm, whereby the MMSCPSO algorithm reduced the active power losses at 18.681% then the PSO algorithm reduced the active power losses at 15.457%. Hence, the MMSCPSO could be a better solution for reactive power optimization in large-scale power systems.

Keywords: Particle swarm optimization (PSO); multi-mean scout particle swarm optimization algorithm (MMSCPSO); reactive power optimization; active power loss; voltage profile improvement.

1. INTRODUCTION

Optimal power flow (OPF) is one of the most crucial keys to the power system operation analysis for not only the security and economic aspects but also for stability and power quality [1]. The optimization of reactive power is very important in electric power systems because it helps to improve the voltage profile and reduce the active power losses of the power system network by satisfying some physical and practical constraints [2].

In power system, proper adjustment of control variables such as generator voltage, transformer tap position, shunt capacitors at a proper value contribute to the control of reactive power within the network. The OPF aims in general to find proper adjustment of aforementioned control variables in order to maintain the voltage at acceptable level and minimize the active power losses [3].

A wide range of conventional optimization techniques have been used to handle the reactive power optimization problem, it has been found that all of these techniques were dealing mainly with continuous variable and they were suffering from convergence toward the local optimal solutions, these methods required some mathematical assumptions such as differential convexity property of the objective function [4],[5]. As the years went by, many researchers got interested in the field of reactive power optimization and proposed various optimization techniques.

C. Mamandur et al. [6], presented a mathematical formulation of the optimal reactive power control (optimal VAR control) for minimizing the active power losses in the electrical system. Utilizing the dual linear programing and employing the method of linearized sensitivity relationship of power system, they have determined the adjustments of control variables.

Ma et al. [7] by considering the non-convex optimization problem even though there are mild condition and saddle point, they have shown that active power losses can be minimized by application of dynamic gradient approach. Amrane and Boundour [8] using the linear decreasing inertia weight, they improved the PSO algorithm for reducing the active power loss in 114-bus Algerian power system and to IEEE 30 and the results werecompared with other algorithms. In [9] Cao et al, presented an algorithm which solves the multi-objective reactive power optimization problem. This algorithm uses an opposition learning as main tool to improve the algorithm’s search efficiency, this technique adopts the inertia weight strategy to balance the global and local exploration. Improvement of particles’ diversity, a modal based crossover, mutation and neighborhood strategy has been used to solve the reactive power problem. Khunkitti et al. [10], based on the weak global search ability of the PSO and good global search ability of dragon fly algorithm (DA), they proposed a hybrid which equilibrate both exploration and exploitation abilities for solving the problem of reactive power optimization within power system. Bansal et al. [11] due to the optimal power flow complexity mathematical formulation, they proposed an algorithm based on modified artificial bee colony by considering the impact of global and local neighborhood for determining the optimal settings of OPF control variables. Zhou et al. [12] solved the optimal power flow problem by proposing new algorithm based on incorporating the cooperation approach within artificial bee colony algorithm to improve its performance. Their method was based on using multiple artificial bee colonies to optimize different components of solution cooperatively for improving the performance of the algorithm in finding optimal solution.

Dai at al. [13] solved the optimal reactive power dispatch (ORPD) problem by using the seeker optimization algorithm (SOA) taking into account the minimization of the active power loss in the transmission network. The proposed algorithm has been evaluated on standard IEEE 57-bus and IEEE 118-bus systems. In addition, the proposed algorithm has been compared to conventional nonlinear programming method, two versions of genetic algorithm (GA), three versions of differential evolution (DE) and four versions of PSO. The simulation results show that the proposed algorithm outperform other algorithms compared with it in terms of balancing global search ability and convergence speed while solving the ORPD problem.

Duman et al. [14] proposed a gravitational search algorithm (GSA) for solving the ORPD problem. The proposed algorithm has been used to determine the settings of control variables including generator terminal voltages, transformer tap settings and reactive power output of the compensating devices with the aim of minimizing the active power loss in the transmission system. The standard IEEE 30-bus, IEEE 57-bus and IEEE 118-bus systems were employed to examine the effectiveness of the proposed algorithm compared to other algorithms found in the literature. The simulation results revealed that the proposed algorithm is robust and effective in solving the ORPD problem.

Sulaiman at al. [15] determined the solution of the ORPD problem by using the gray wolf optimizer (GWO) considering the minimization of the active power loss and minimization of voltage deviation. The proposed algorithm has been employed to determine the best combination of control variables including generator voltages, tap changing transformer's ratios and the amount of reactive compensation devices. The performance of the proposed algorithm has been tested on IEEE 30-bus and IEEE 118-bus systems. The simulation results show that the proposed algorithm yielded better results compared to other algorithms compared with it in solving the ORPD problem.

Mei et al. [16] utilized the moth-flame optimization algorithm (MFO) to address the ORPD problem considering the minimization of the power loss and minimization of voltage deviation. They tested their algorithms on IEEE 30-bus, IEEE 57-bus and IEEE 118-bus systems. The proposed algorithm has been compared to other algorithms surfaced in the literature and yielded promising results.

In the present work, the multi-mean scout particle swarm optimization (MMSCPSO) algorithm is implemented on IEEE 118 bus test power system and the aim is to prove its performance in comparison with other algorithms presented in the literature review. The main objective was to minimize the active power losses by improving the voltage profile of the power system.

The rest of this paper is arranged as follows:

Section 2 presents the optimal power flow problem formulation, Section 3 presents PSO algorithm, Section 4 describes the ABC algorithm, Section 5 details the method proposed for optimizing the reactive power in large-scale power systems. Section 6 consists of simulation results and discussion, and at the end an overall conclusion is drawn in Section 7.

2. PROBLEM FORMULATION

The reactive power optimization problem is mainly formulated as minimization of total active power losses of the whole electric power system. The objective fiction is mathematically stated as follows:

$$f_1 = \min\left\{ P_{loss} = \sum_{k=1}^{Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij} \right) \right\} \quad (1)$$

Where P_{loss} is the total active power loss, V_i, V_j are voltages of i[th] and j[th] buses respectively, θ_i, θ_j are voltage angles of i[th] and j[th] buses, g_k is the branch conductance.

The objective function is subjected to different constraints.

2.1 Equality Constraints

The equality constraints were satisfied by Newton Raphson load flow algorithm:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{N_{bus}} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) = 0, \quad i \in N_{bus} \quad (2)$$

$$Q_{G_i} + Q_{c_i} - Q_{D_i} - V_i \sum_{j=1}^{N_{bus}} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) = 0, \quad i \in N_{bus} \tag{3}$$

Where P_{G_i} is the active power at i[th] generator bus, Q_{G_i} the reactive power at i[th] generator bus, Q_{C_i} is the reactive power of shunt capacitor at i[th] bus, G_{ij} is the transfer conductance, B_{ij} is the transfer susceptance and N_{bus} is the bus number.

2.2 Inequality Constraint

- Non-control variables:

$$V_{L_i}^{\min} < V_{L_i} < V_{L_i}^{\max}, \quad i = 1,2,3,......N_{PQ} \tag{4}$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, \quad i = 1,2,3,......N_g \tag{5}$$

Where $V_{L_I}^{\min}$ is the minimum voltage at i[th] load bus, $V_{L_i}^{\max}$ is the maximum voltage at i[th] load bus, V_{L_i} is the voltage at i[th] load bus, $Q_{g_i}^{\min}$ is the minimum reactive power at i[th] generator bus, $Q_{g_i}^{\max}$ is the maximum reactive power at i[th] generator bus, Q_{g_i} is the reactive power at i[th] generator bus, N_{PQ} is the number of load buses and N_g is the number of generator buses.

- Control variables:

$$V_{gi}^{\min} < V_{gi} < V_{gi}^{\max}, \quad i = 1,2,3,......N_g \tag{6}$$

$$T_i^{\min} < T_i < T_i^{\max}, \quad i = 1,2,3,......N_T \tag{7}$$

$$Q_{ci}^{\min} < Q_{ci} < Q_{ci}^{\max}, \quad i = 1,2,3,......N_{Q_C} \tag{8}$$

Where V_{g_i} is the voltage at i[th] generator bus, $V_{g_i}^{\min}$ is the minimum voltage at i[th] generator bus, $V_{g_i}^{\max}$ is the maximum voltage at i[th] generator bus, T_i is the transformer tap position at i[th] bus, $T_i^{\min}$ is the minimum value of transformer tap position at i[th] bus, $T_i^{\max}$ is the maximum value of transformer tap position at i[th] bus, Q_{c_i} is the reactive power of shunt capacitor at i[th] bus, $Q_{c_i}^{\min}$ is the minimum reactive power of the shunt capacitor at i[th] bus, $Q_{c_i}^{\max}$ is the maximum reactive power of the shunt capacitor at i[th] bus.

The vector of independent variables (or control) variables is represented in eq.9 whereas the vector of dependent variable (or non-control variables) is presented in eq.10.

$$u^T = \left[V_{g_1},......,V_{g_{N_g}}, T_1,......T_{N_T}, Q_{c_1},......Q_{c_{N_C}} \right] \tag{9}$$

$$x^T = \left[V_{L_1},......,V_{L_{N_{PQ}}}, Q_{g_1},......Q_{g_{N_g}} \right] \tag{10}$$

The augmented objective function is shown in eq.11.

$$F = f_1 + \sum_{i=1}^{N_{PQ}^{\lim}} \lambda_{V_L} \left(V_{L_i} - V_{L_i}^{\lim} \right)^2 + \sum_{i=1}^{N_g^{\lim}} \lambda_{Q_g} \left(Q_{gi} - Q_{gi}^{\lim} \right)^2 \tag{11}$$

The augmented objective function is shown in eq.11.

Where F is the augmented objective function, f_1 is the power loss, λ_{V_L} is the penalty factor for load bus voltage violating its limits, λ_{Q_g} is the penalty factor for generator bus violating its limits, V_{L_i} is the voltage at i[th] load bus, $V_{L_i}^{\lim}$ is the voltage limit at i[th] load bus, $Q_{g_i}^{\lim}$ is the reactive power limit at generator bus, $N_{PQ}^{\lim}$ is the number of load buses violating their limits, $N_g^{\lim}$ is the number of generator buses violating its limits.

3. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization is a population-based belonging in the class of metaheuristics. It was firstly introduced in 1995 by James Kennedy (social psychologist) and RusselEberhart (electrical engineer) [17]. The PSO development was based on the social behavior of birds flocking or fish schooling searching for the food and this algorithm is applicable in various fields including engineering fields due to its simplicity and efficacy in implementation [18]. In the PSO algorithm the search process is conducted by particles grouped in a swarm where each particle is representing a candidate solution and particles update the velocity and position according to eq.12 and eq.13 respectively.

$$v_{id}^{(k+1)} = wv_{id}^{(k)} + c_1 r_1 \left(p_{id}^{(k)} - x_{id}^{(k)} \right) + c_2 r_2 \left(p_g^{(k)} - x_{id}^{(k)} \right) \quad (12)$$

$$v_{id}^{(k+1)} = wv_{id}^{(k)} + c_1 r_1 \left(p_{id}^{(k)} - x_{id}^{(k)} \right) + c_2 r_2 \left(p_g^{(k)} - x_{id}^{(k)} \right) \quad (13)$$

Where x_{id} is the position of i[th] particle in d-dimension, v_{id} is the velocity of i[th] particle in d-dimension, r_1, r_2 are random numbers, c_1, c_2 are acceleration coefficients, w is the inertia factor, p_{id} is the personal best position of i[th] particle in d-dimension, p_g is the global best position of particle.

4. ARTIFICIAL BEE COLONY (ABC)

Artificial Bee Colony Algorithm is one of the intelligent algorithms belonging in the class of metaheuristic, it was proposed for the first time by Dervis Karaboga in 2005. It depicts the behavior of natural behavior of real honey bees in food foraging [19]. Basically, the ABC has four phases which are as follows: the first phase is the initialization phase, the second is employee bee phase, the third is onlooker bee phase and the forth is scout bee phase [20]. The employed bees search for neighborhood solution based on eq.14 and through the waggle dance in the hive they share information with onlooker bees which choose the best source based on the efficiency of the source (fitness) and on probability (potential in having good nectar) as presented in eq.15 and eq.16 respectively [17],[18]. After a given number of iterations, the food sources which are no longer having nectar are replaced by new ones as in eq.14.

$$v_{ij} = x_{ij} + \phi_{ij} \left(x_{ij} - x_{kj} \right), \quad j \neq k \quad (14)$$

$$fit(x_i) = \begin{cases} \dfrac{1}{\left(1 + f(x_i)\right)} & if \quad f(x_i) \geq 0 \\ 1 + abs\left(f(x_i)\right) & if \quad f(x_i) < 0 \end{cases} \quad (15)$$

$$p_i = \frac{fit(x_i)}{\sum fit(xi)} \quad (16)$$

Where the parameter ϕ_{ij} is chosen in the interval $[-1,1]$, x_{ij} is the i[th] reference food source, x_{kj} is a random selected food source, v_{ij} is new solution, $fit(x)$ is the fitness function and $f(x_i)$ is the function of i[th] food source, p_i is the probability of the i[th] source.

5. METHODS

Based on the drawbacks and handicap of PSO, this paper proposes a new hybrid called “multi-mean scout particle swarm optimization (MMSCPSO)” which combines both PSO and ABC algorithms to perform the reactive power optimization in large-scale power systems. In the standard PSO all particles generated remains in the search space during the whole search process and these ones do not get replaced even though they do not improve their objective functions (fitness) after many iterations. The MMSCPSO introduces an alleviation to this scenario whereby population is generated by both tent and logistic maps as shown in eq.17 and eq.18 respectively, as the initial population plays a significant role in metaheuristic algorithm for achieving the global solution. These two chaotic maps allow the particle to be well dispatched within the search space to facilitate the global search. Introduction of the scout phase allows the replacement of particles which are not able to improve their fitness after several iterations (idle particles). This mechanism allows the algorithm to achieve the balance of both exploration and exploitation abilities so that the optimal solution can be easily found. The flow chart of the MMSCPSO is shown in the Fig.1.

$$\begin{aligned} x_{n+1} &= \mu x_n \left(1 - x_n\right), \quad \mu = 4 \\ 0 &< x_0 < 1 \end{aligned} \quad (17)$$

$$x_{n+1} = \begin{cases} \lambda x_n, & 0 \leq x_n \leq 1/2, \quad \lambda = 2 \\ \lambda\left(1 - x_n\right), & 1/2 \leq x_n \leq 1 \end{cases} \quad (18)$$

Where x_0 is the initial vector, x_n is the vector at n[th] iteration. The eq.19 shows the improvement of velocity equation while the particles are performing the search for global solution. Velocity equation becomes:

$$v_{id}^{(k+1)} = w \times v + c_1 r_1 \left(p_{mean,d}^{k} - x_{id}^{k} \right) + c_2 r_2 \left(p_{g\_subswarm}^{k} - x_{id}^{k} \right) + c_3 r_3 \left(p_{g\_swarm}^{k} - x_{id}^{k} \right), \quad c_2 = c_3 \tag{19}$$

Where $p_{mean,d}^{k}$ is the mean value of personal best of the subswarm at k[th] iteration, $p_{g\_subswarm}^{k}$ is the global best of the subswarm, $p_{g\_swarm}^{k}$ is the global best of the whole swarm.

In this scenario, particles are subdivided into subswarm so that to allow them to learn from the mean value of personal best of the subswarm and the global best of the whole swarm in order to improve the communication among particles during the search. r_1 , r_2 and r_3 are obtained by using both tent and logistic maps. Then acceleration factors c_1 , c_2 and c_3 are obtained as shown in eq.20 and eq.21 respectively whereby $c_2 = c_3$.

$$c_1 = c_{final} - \left(c_{final} - c_{initial} \right) * \left(\frac{\max_{iter} - iter}{\max_{iter}} \right) \tag{20}$$

$$c_2 = c_{initial} + \left(c_{final} - c_{initial} \right) * \left(\frac{\max_{iter} - iter}{\max_{iter}} \right), c_2 = c_3 \tag{21}$$

Where c_{final} is the maximum value of acceleration factor, $c_{initial}$ is the minimum value of acceleration factor, $\max_{iter}$ is the maximum number of iteration and $iter$ is the current iteration.

The inertia weight factor plays an important role in controlling the previous velocity of particles. It is calculated by using eq.22:

$$w = w_{\max} - \left(w_{\max} - w_{\min} \right) * \left(\frac{\max_{iter} - iter}{\max_{iter}} \right) \tag{22}$$

Where w is the inertia weight factor, $w_{\min}$ is the minimum inertia weight, $w_{\max}$ is the maximum inertia weight.

6. RESULTS AND DISCUSSION

This section presents the results carried out on IEEE 118-bus system by using the proposed MMSCPSO algorithm whereby the main purpose is to determine good settings of control variables which are voltages at all generator buses (V_g), tap position of transformers (T) and shunt capacitor (Q_c) connected in the system so that to minimize the total active power of the network. This network comprises 1 slack bus (reference bus), 53 voltage-controlled buses or PV buses among which there are 18 generators and 35 synchronous condensers, 64 load buses or PQ buses, 177 transmission lines, 9 transformers and 14 shunt capacitors/reactors. The system loads total active power and total reactive power are 4242 MW and 1438 Mvars respectively. The total active power and reactive power losses of the system obtained by applying Newton Raphson are 133.694 MW and 796.372 Mvars. The system has 77 dimensions/variables namely voltage generator buses, transformer tap position and shunt capacitors/reactors. The step size for transformer tap position is 0.01 p.u whereas the step size for switchable shunt capacitor is 5 Mvar.

The Table 1. shows the results obtained after implementing both PSO and MMSCPSO algorithms for different control variables located at different buses as indicated in the table.

The voltage profile has improved as shown in Fig. 2 which compares the base case (Newton Raphson), PSO and MMSCPSO algorithms.

The Fig. 3 illustrates the loss minimization comparing both PSO and MMSCPSO algorithms.

After conducting 20 runs both PSO and MMSCPSO algorithms have been compared to show the outperformance of MMSCPSO in terms of both accuracy and convergence as shown in Table 2. The worst loss shows the maximum value of active power loss among those 20 runs, the best loss shows the minimum value of active power loss and the mean value represents the active power loss obtained by using Newton Raphson algorithm computation. The table also captures other values of losses obtained in the researches mentioned in the literature review to prove the efficacy of the method proposed for minimizing the active power in the power system.

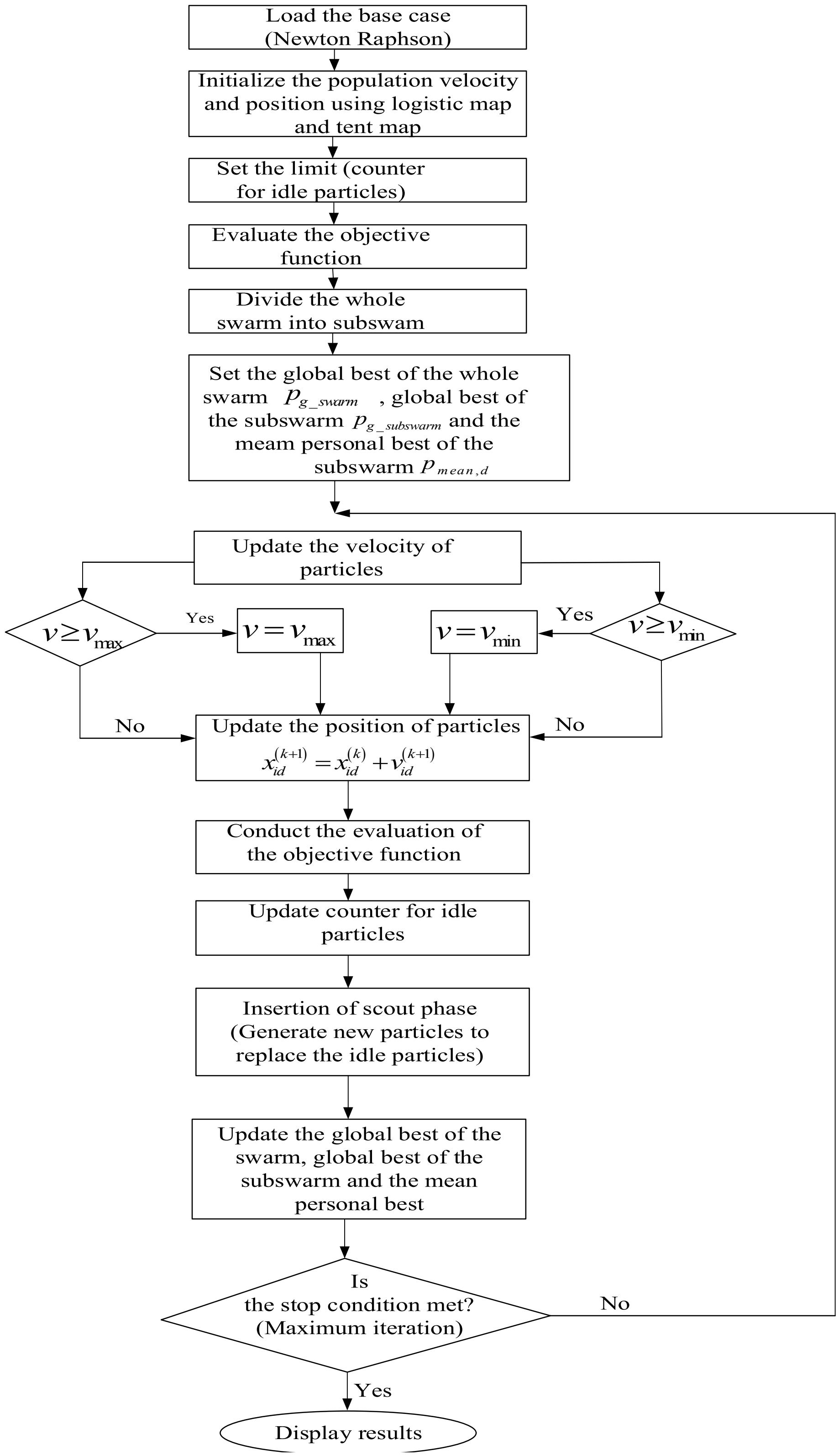

Fig. 1. The flow chart for the MMSCPSO

Table1. Control variables and their respective maximum and minimum values before and after optimization case of IEEE 118-bus system

S/N	Control Variables	Voltage in p.u before optimization	Voltage in p.u after optimization by PSO	Voltage in p.u after optimization by MMSCPSO	Minimum	Maximum
1	Vg1	0.9550	1.0405	1.0593	0.95 p.u	1.1 p.u
2	Vg4	0.9980	1.0645	1.0847	0.95 p.u	1.1 p.u
3	Vg6	0.9900	1.0497	1.0788	0.95 p.u	1.1 p.u
4	Vg8	1.0150	1.0604	1.0599	0.95 p.u	1.1 p.u
5	Vg10	1.0500	1.1000	1.0697	0.95 p.u	1.1 p.u
6	Vg12	0.9900	1.0480	1.0723	0.95 p.u	1.1 p.u
7	Vg15	0.9700	1.0450	1.0678	0.95 p.u	1.1 p.u
8	Vg18	0.9730	1.0369	1.0719	0.95 p.u	1.1 p.u
9	Vg19	0.9630	1.0372	1.0675	0.95 p.u	1.1 p.u
10	Vg24	0.9920	1.0565	1.0714	0.95 p.u	1.1 p.u
11	Vg25	1.0500	1.1000	1.0975	0.95 p.u	1.1 p.u
12	Vg26	1.0150	1.1000	1.1000	0.95 p.u	1.1 p.u
13	Vg27	0.9680	1.0588	1.0629	0.95 p.u	1.1 p.u
14	Vg31	0.9670	1.0488	1.0579	0.95 p.u	1.1 p.u
15	Vg32	0.9640	1.0479	1.0600	0.95 p.u	1.1 p.u
16	Vg34	0.9860	1.0574	1.0784	0.95 p.u	1.1 p.u
17	Vg36	0.9800	1.0585	1.0742	0.95 p.u	1.1 p.u
18	Vg40	0.9700	1.0339	1.0493	0.95 p.u	1.1 p.u
19	Vg42	0.9850	1.0355	1.0555	0.95 p.u	1.1 p.u
20	Vg46	1.0050	1.0663	1.0735	0.95 p.u	1.1 p.u
21	Vg49	1.0250	1.0699	1.0901	0.95 p.u	1.1 p.u
22	Vg54	0.9550	1.0346	1.0658	0.95 p.u	1.1 p.u
23	Vg55	0.9520	1.0326	1.0634	0.95 p.u	1.1 p.u
24	Vg56	0.9540	1.0349	1.0649	0.95 p.u	1.1 p.u
25	Vg59	0.9850	1.0499	1.0857	0.95 p.u	1.1 p.u
26	Vg61	0.9950	1.0598	1.0882	0.95 p.u	1.1 p.u
27	Vg62	0.9980	1.0457	1.0827	0.95 p.u	1.1 p.u
28	Vg65	1.0050	1.0743	1.0777	0.95 p.u	1.1 p.u
29	Vg66	1.0500	1.0700	1.1000	0.95 p.u	1.1 p.u
30	Vg69	1.0350	1.0874	1.1000	0.95 p.u	1.1 p.u
31	Vg70	0.9840	1.0480	1.0696	0.95 p.u	1.1 p.u
32	Vg72	0.9800	1.0334	1.0587	0.95 p.u	1.1 p.u
33	Vg73	0.9910	1.0382	1.0629	0.95 p.u	1.1 p.u
34	Vg74	0.9580	1.0268	1.0563	0.95 p.u	1.1 p.u
35	Vg76	0.9430	1.0405	1.0640	0.95 p.u	1.1 p.u
36	Vg77	1.0060	1.0739	1.0820	0.95 p.u	1.1 p.u
37	Vg80	1.0400	1.0861	1.0945	0.95 p.u	1.1 p.u
38	Vg85	0.9850	1.0977	1.0990	0.95 p.u	1.1 p.u
39	Vg87	1.0150	1.0266	1.0755	0.95 p.u	1.1 p.u
40	Vg89	1.0050	1.1000	1.0997	0.95 p.u	1.1 p.u
41	Vg90	0.9850	1.0722	1.0802	0.95 p.u	1.1 p.u
42	Vg91	0.9800	1.0730	1.0891	0.95 p.u	1.1 p.u
43	Vg92	0.9930	1.0892	1.0993	0.95 p.u	1.1 p.u
44	Vg99	1.0100	1.0639	1.0861	0.95 p.u	1.1 p.u
45	Vg100	1.0170	1.0756	1.0926	0.95 p.u	1.1 p.u
46	Vg103	1.0010	1.0611	1.0795	0.95 p.u	1.1 p.u
47	Vg104	0.9710	1.0559	1.0673	0.95 p.u	1.1 p.u
48	Vg105	0.9650	1.0553	1.0660	0.95 p.u	1.1 p.u
49	Vg107	0.9520	1.0414	1.0583	0.95 p.u	1.1 p.u
50	Vg110	0.9730	1.0424	1.0609	0.95 p.u	1.1 p.u

51	Vg111	0.9800	1.0397	1.0665	0.95 p.u	1.1 p.u
52	Vg112	0.9750	1.0272	1.0471	0.95 p.u	1.1 p.u
53	Vg113	0.9930	1.0531	1.0789	0.95 p.u	1.1 p.u
54	Vg116	1.0050	1.0674	1.0721	0.95 p.u	1.1 p.u
55	T8-5	0.9850	1.1000	0.9800	0.9	1.1
56	T26-25	0.9600	1.0500	1.0700	0.9	1.1
57	T30-17	0.9600	1.1000	1.0500	0.9	1.1
58	T38-37	0.9350	0.9000	1.0200	0.9	1.1
59	T63-59	0.9600	0.9000	1.0700	0.9	1.1
60	T64-61	0.9850	1.1000	1.0600	0.9	1.1
61	T65-66	0.9350	0.9000	1.0300	0.9	1.1
62	T68-69	0.9350	0.9000	1.0300	0.9	1.1
63	T81-80	0.9350	0.9000	1.0600	0.9	1.1
64	Qc5	-40	25	25	0Mvar	25Mvars
65	Qc34	14	25	25	0Mvar	25Mvars
66	Qc37	-25	15	25	0Mvar	25Mvars
67	Qc44	10	25	15	0Mvar	25Mvars
68	Qc45	10	0	0	0Mvar	25Mvars
69	Qc46	10	0	5	0Mvar	25Mvars
70	Qc48	15	25	5	0Mvar	25Mvars
71	Qc74	12	25	25	0Mvar	25Mvars
72	Qc79	20	0	0	0Mvar	25Mvars
73	Qc82	20	10	25	0Mvar	25Mvars
74	Qc83	10	20	25	0Mvar	25Mvars
75	Qc105	20	10	0	0Mvar	25Mvars
76	Qc107	6	0	10	0Mvar	25Mvars
77	Qc110	6	25	10	0Mvar	25Mvars

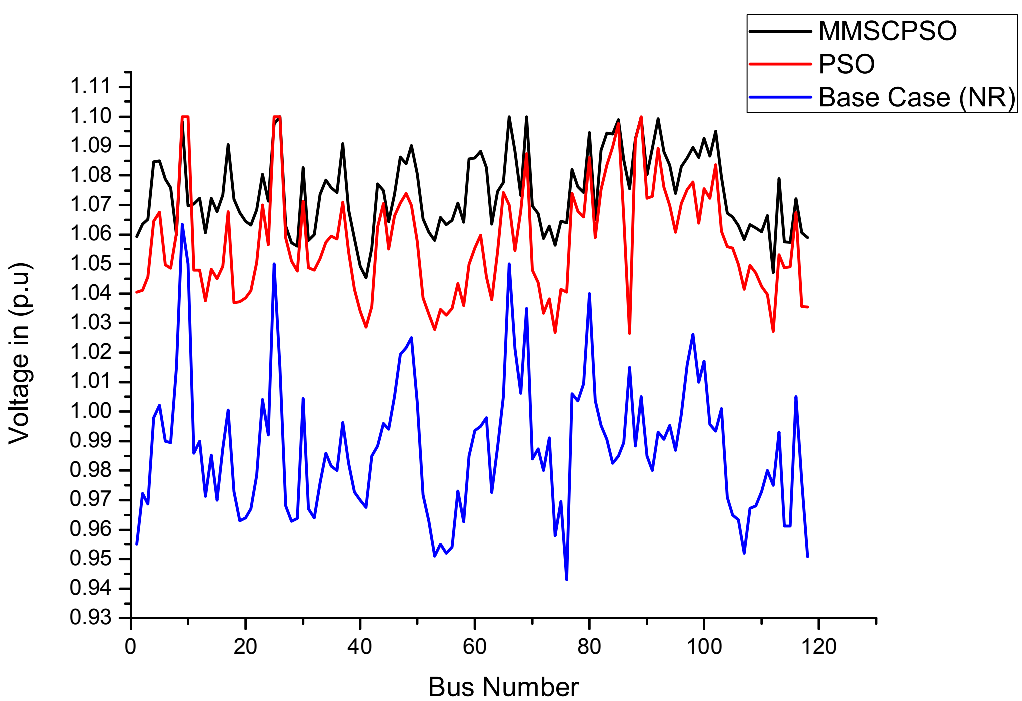

Fig. 2. Voltage improvement at all buses before and after optimization for IEEE 118-bus system

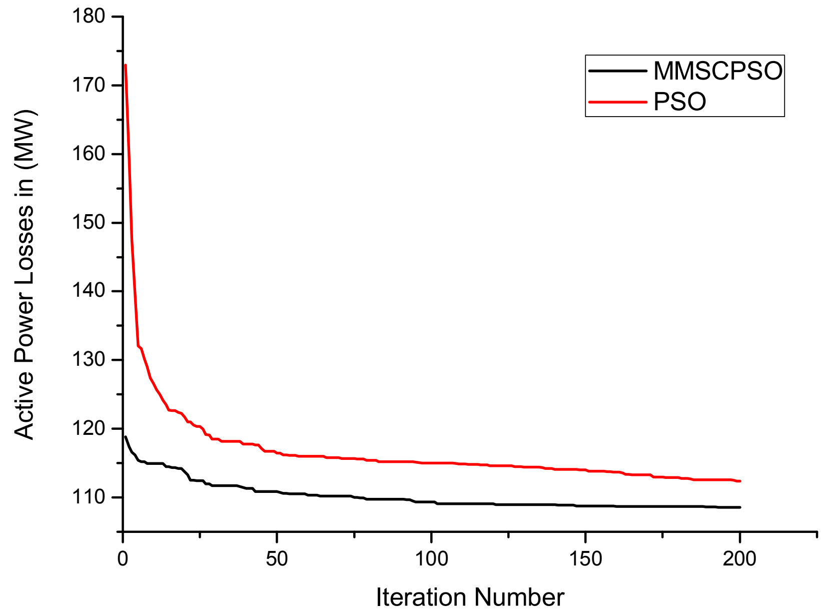

Fig. 3. Active power loss minimization in IEEE 118-bus system

Table 2. Comparison of algorithms performance

ALGORITHM	**ACTIVE POWER LOSS (MW)**			**Standard Deviation (SD)**
	Worst Loss	**Best loss**	**Mean loss**	
Base Case (NR)	-	-	133.694	-
PSO	172.9232	112.4116	113.0280	$5.322x10^{-3}$
MMSCPSO	118.8206	108.5942	108.7185	$2.234x10^{-4}$
SOA	116.34725	114.95013	115.67443	$3.5908x10^{-3}$
GSA	-	127.7603	-	-
GWO	-	120.65	-	-
MFO	-	116.4254	-	-

7. CONCLUSION

This paper has dealt with reactive power optimization where the main objective function was the minimization of reactive power within large-scale electric power systems. Various constraints were also considered, the equality constraints were satisfied by Newton Raphson load flow computation whereas inequality constraints were transformed into equality constraints and were being added to the main objective function in form of penalty function so as to penalize those violating their limits. The objectives of the research were achieved because both PSO and MMSCPSO algorithms were successfully developed, implemented in MATLAB 2015(a) and were applied on IEEE 118-bus system to ensure the optimization of reactive power by not only fine-tuning the control variables (voltage at generator bus, transformer tap position and shunt capacitor), reducing the entire active power losses of the system but also improving the voltage profile of all buses. For the case of IEEE 118-bus system, using the PSO algorithm the active power losses have reduced from 133.694MW up to 112.4116MW which means 15.457% of loss reduction whereas using MMSCPSO the active power losses have reduced up to 108.5942MW which means 18.681% of loss reduction. As the results have been shown the MMSCPSO algorithm outperformed the standard PSO algorithm, and this was due to two main modifications made. Initialization of initial population by using chaotic map (logistic map and tent map) have had a great impact in letting particles being well spread all over the search space compared to uniform random distribution as to increase not only the diversity but also the chance of find good optimal solution. The insertion of scout phase has also brought big contribution because it has alleviated the handicap of PSO by sustaining the resurgence of idle particles (particles unable to improve their personal best position) and this has contributed in balancing the exploration and exploitation abilities of the algorithm. The method proposed illustrated also good performance in terms of active power minimization as it obtained the best value of losses comparing with other algorithms cited in literature review.

For future work, the MMSCPSO will be applied to other power system optimization problems such as optimal reactive power dispatch (ORPD) problem considering FACTS, ORPD problem considering the impact of renewable energy sources, etc. In addition, other chaotic maps including Gauss/mouse map, Chebychev map, Liebovitch map, sine map and sinusoidal map may be employed to examine their impact on the performance of the MMSCPSO.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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