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Reactive Power Optimization Based on Artificial Intelligence

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Abstract

The losses in electrical power systems are a great problem. Multi methodology is utilized to decrease power losses in transmission line. Reactive power optimization problem is really part of optimal load flow calculation where the adjusting of reactive power is one of the ways for minimizing the losses in any power system. In this study, we have presented three types of Particle Swarm Optimization (PSO) algorithm to solve reactive power optimization problem, and compared the results of these approaches with some results reported in the literature. The first type is by using Simple PSO, the second type is by using Modified PSO (MPSO), and the last type is by using Chaotic PSO (CPSO), and the CPSO can enhance performance of convergence, the accuracy and decrease the calculation time for the Simple PSO algorithm. All these algorithm types have been applied to the IEEE-57 node and IEEE-118 node systems for power loss minimization in lines and to keep the voltage at all nodes with an acceptable bound and stay the power system employing under normal conditions.

Keywords: Reactive power optimization, Optimal Load Flow, PSO, MPSO, CPSO

INTRODUCTION

Studies estimated about 70% of the total power losses are in the distribution systems [1]. The aims of reactive power optimization problem are to keep voltage at all nodes within an acceptable bound and minimize the system loss. The reactive power optimization problem is necessary for power quality, system stability and ideal operation of electrical power systems. Reactive power problem dealed with regulating generator voltages node (VG), transformers tap ratio (Tap), and shunt VAR source (capacitors/reactors) which can generate or absorb reactive power, so as to reallocate the reactive power of a generation units in the power system. Several approaches are utilized for solving reactive power problem for examples, interior point method, genetic algorithm, dynamic, quadratic, linear and nonlinear programing [2–6].

Carpentier was introduced the optimal power flow calculations in year 1962s [7]. Moreover, in the last years, bacterial chemotaxis, differential evolution, ant colony, Particle Swarm Optimization (PSO) and different intelligence computation approaches have been suggested for solving the reactive power optimization [8–11].

For decreasing real power loss a dynamic weights based PSO algorithm has been presented on standard IEEE 6-node system in reference [12]. For decreasing the cost of generators and reactive compensators, PSO based reactive power optimization approach has been used [13]. In another study, a modified artificial fish swarm (MAFSA) algorithm has been applied to solve reactive power optimization and this approach has been presented on standard IEEE -57 node system [14].

A seeker optimization algorithm has been used for reactive power dispatch problem; the researchers presented this approach to several functions and this approach is applied on IEEE -57 and -118 node systems as well as the findings are compared with different conventional non-linear programming approaches (for example GA, DE, and PSO) [15].

The GA was implemented to solve the problem of reactive power flow optimization in a power system [16]. Three hybrid algorithms (GA, SA and TS) have been implemented for reactive power optimisation by adjusting voltage at generators node, tap ratio of transformers and the VAR sources rectors/capacitors [17].

In this study, Simple PSO has been developed to solve the reactive power optimization problem for minimizing power losses and voltage profile enhancement, so as to improve the searching quality of Simple PSO algorithm and to avoid a drop into the elementary convergence to local minima and to decrease the calculation time, Chaotic PSO (CPSO) is utilize so as to overcome this disadvantage. The chaos greatly enables CPSO to escape from the local minima. Simple PSO, MPSO and CPSO are applied for solving reactive power optimization problem on IEEE-57 node system and -118 node system. The simulation results prove that the findings obtained in CPSO algorithm is the best results were compared with the Simple PSO, MPSO and the results that obtained in the other papers.

PROBLEM FORMULATION

Reactive power optimization problem

The great aim of the objective function for reactive power optimization is to decrease the power loss of branches through the ideal correction of power system control parameters and at the same time dealing with equality and unequal constrains [18-21].

Mathematical problem formulation

The equation of power losses can be express as follows [18]:

$$Min\ P_{loss} = f(x_1, x_2) = \sum_{K=1}^{Ntl} G_K(V_i^2 + V_j^2 - 2V_iV_i cos(\phi_i - \phi_j) \quad (1)$$

$$Subjected\ to\ g(x_1, x_2) = 0 \quad (2)$$

$$h(x_1, x_2) \leq 0 \quad (3)$$

$f(x_1, x_2)$ is the real power loss function of the system; G_K is the conductance of $K - th$ line; V_i is the voltage of i −node and V_j is the voltage of j −node; Ntl represent the number of branches; ϕ_i and ϕ_j are the angles of voltage at nodes i and j, respectively; $g(x_1, x_2)$ represents the load flow equations; $h(x_1, x_2)$ represent the inequality constrains and $x_1^T = [V_L\ Q_G]$ is the vector of dependent variables involving:

1. Voltage at load node (V_L).
2. Generated reactive power (Q_G).

Aand $x_2^T = [V_G\ \ Tap\ \ Q_C]$ is the vector of independent variables and consisting of:

1. Voltage at generator node V_G (continuous).
2. Transformer taps settings Tap (discrete).
3. Shunt capacitors VAR compensation Q_C (discrete).

Constrains

Equality constrains: These constrains are the load flow equations which can be express as shown below [18]:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j(G_{ij} cos(\phi_{ij}) + B_{ij} sin(\phi_{ij}) = 0 \quad (4)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j(G_{ij} sin(\phi_{ij}) - B_{ij} cos(\phi_{ij}) = 0 \quad (5)$$

NB is the number of nodes in the system; P_{Gi} is the real power and Q_{Gi} is the output reactive power of generator at node i; P_{Di} is the load active power and Q_{Di} is the load reactive power at node i; G_{ij} is the mutual conductance among i node and j node and B_{ij} is the mutual susceptance among i node and j node; V_i is the voltage value in i node and V_j is the voltage value in j node; ϕ_{ij} is the voltage angle difference in node i and node j.

Inequality constrains: this constrain include [18]:

1. Constrains of generator: these constrains have voltage in generator nodes V_G and reactive power output Q_G of all generators are limited by their min and max bounds:

$$V_{Gi-min} \leq V_{Gi} \leq V_{Gi-max}, \quad i = 1, \dots \dots, N_G \quad (6)$$

$$Q_{Gi-min} \leq Q_{Gi} \leq Q_{Gi-max}, \quad i = 1, \dots \dots, N_G \quad (7)$$

2. Transformer constrains: this constrains have lower and upper bounds as shown below:

$$Tap_{\ i-min} \leq Tap_{\ i} \leq Tap_{\ i-max} \quad i = 1, \dots \dots, N_T \quad (8)$$

3. Shunt VAR source Q_C constrains: switch-able VAR compensation Q_C are bounded as shown below:

$$Q_{Ci-min} \leq Q_{Ci} \leq Q_{Ci-max} \quad i = 1, \dots \dots, N_T \quad (9)$$

4. Security constrains: this constrain contain the limit of load node voltages as shown below:

$$V_{Li-min} \leq V_{Li} \leq V_{Li-max} \quad i = 1, \dots \dots, N_{PQ} \quad (10)$$

Objective functions

In this problem, the dependent variables can be added to equation (1) by utilizing penalty factors to constrain, so equation (1) can be represented as shown below [18]:

$$F = P_{loss} + \lambda_V \sum_{i=1}^{NL} (v_{Li} - v_{Li}{}^{lim})^{\ 2} + \lambda_Q \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}{}^{lim})^{\ 2} \quad (11)$$

λ_V and λ_Q are penalty terms; $X^{\lim}$ is the limit value of inequality constrains; NL is the total number of load nodes; NG is the numbers of generation station and P_{loss} is given in equation (1).

Concept of Average Voltage

In this study, the new average voltage index is suggested to deal with all voltage nodes and satisfy most of the electrical utility limits. The equation of this concept can be written as shown below:

$$V_{av} = \frac{\sum_{i=1}^{Nn} V_i}{N_n} \quad (12)$$

from the above equation, V_{av} is the average voltage of the system; the voltage in node i is V_i and the total numbers of nodes is N_n.

OPTIMIZATION PROCESS

(PSO) algorithm

This algorithm is a kind of stochastic optimization, it is fast, simple, robust, high flexibility, guarantees the results convergence, differs from Genetic Algorithm (GA) that does not contains crossover and mutation. It was usually applied for continuous non-linear problem. Eberhart and Kennedy have been first proposed PSO in year 1995 [22]. PSO approach was developed as an optimization technique, and it has been describe the behavior of group such as flock school fish or swarms of birds. PSO is initialized to a group of random agents, all agents have a fitness determined by a fitness function every agent has a speed factor to determine its flight direction and distance. Then it discovers optimal solution by iteration. In each iteration, the agents change themselves by tracking two extremism, one of them is the optimal solution found by the agent itself, it is called best position (p_{bi}), and the other is the optimal solution found by all agents, it is called global best position (g_{bi}). The agents change their speed and position by utilizing equation (13) and equation (14) [23,24]:

$$v_i^{k+1} = K*[w * v_i^k + c_1old * rand_1*(p_{bi}^k - x_i^k) + c_2old*rand_2*(g_{bi}^k - x_i^k)] \quad (13)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (14)$$

where:

v : is the velocity of agent .

W : is the weight of agent.

c_1 old and c_2 old: are the old constant learning factors between $[0 - 2.05]$.

$rand_1$ and $rand_2$: are the uniformly distributed positive number within limit $[0 - 1]$.

P_{bi} : is the best position of agent.

g_{bi} : is the global best position of agents.

X_i : is the position of agent.

K : is the constriction factor and it is utilize so as to get better convergence of the algorithm, and it can be express as shown below [25]:

$$K = \frac{2}{\left|2-\phi-\sqrt{\phi^2-4\phi}\right|}, \qquad \phi = c_1 + c_2,\ \phi \geq 4 \quad (15)$$

Now, (W) given in (13), is reducing linearly from (0.9 to 0.4) by increasing the iteration so as to make the balancing between P_{bi} and g_{bi} position as follows:

$$W = W_{max} - \frac{W_{max} - W_{min}}{max_{iteration}} * iter \quad (16)$$

from the above equation:

W_{max}: is the max. inertia.

W_{min}: is the min. inertia.

$iter$: is the present iteration.

$max_{iteration}$: is the max. iterations.

(MPSO) algorithm

In this approach, agents move to be nearest to the better position and discover the global minimum point [26]. The bad finding is neglected but the good finding is stored and recorded as the optimal finding unless a good one is found, and is represented by best position (p_{bi}). Thus far, the best global best position of the swarm is recorded as global position (g_{bi}). The equations for the MPSO are as shown below:

$$v_i^{k+1} = w * v_i^k + c_1\text{new} * rand_1*(p_{bi}^k - x_i^k) + c_2\text{new}*rand_2*(g_{bi}^k - x_i^k) \quad (17)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (18)$$

$$c_1new = rand() \quad (19)$$

$$c_2new = rand() \quad (20)$$

The new learning factors given in equations (19) and (20) are modified to a random values within range [0,1] instead of (c_1 old and c_2 old) constant value in PSO. When using c_1new and c_2new in MPSO raises the probability of simple PSO to discover the optimal solution faster than (c_1 *old* and c_2 *old*) constant values given in simple PSO and w is defined as given in equation (16).

(CPSO) algorithm

The simple PSO algorithm mainly relies on its parameters, and this made it difficult and sometimes unable to reach the accurate solution criteria in some cases, especially when the number of parameters of the optimization problem is relatively large. So as to overcome this drawback, PSO and chaos theory merged to form a hybrid algorithm called CPSO algorithm, and this way helped the CPSO algorithm to slip from the local optima due to the special behavior and high ability of the chaos [27]. In this study, the logistic sequence equation adopted for constructing the hybrid CPSO algorithm is shown in the below equation [28]:

$$\beta^{k+1} = \mu\beta^k((1 - \beta^k)), \qquad 0 \leq \beta^1 \leq 1 \quad (21)$$

From equation (21), the control parameter μ is set within a range [0.0−4.0], k is the number of the iterations. The value of μ decides whether β stabilizes at a constant area, oscillates within restricted limits, or behaves chaotically in an unpredictable form. And equation (21) is deterministic, it shows chaotic dynamics when $\mu = 4.0$ and β^1 € $\{0,0.25,0.5,0.75,1\}$. It shows the sensitive depends on its initial conditions, which is the basic characteristic of chaos. The new inertia weight factor (W_{CPSO}) is calculated by multiplying the (W) in equation (16) and logistic sequence in equation (21) as follows:

$$W_{CPSO} = W * \beta^{k+1} \quad (22)$$

To improve the behavior of the simple PSO, this study introduces a new velocity change by incorporating a logistic sequence equation with inertia weight factor. Finally, by substituting equation (22) with equation (13), the following velocity updated equation for the proposed technique is defined as shown below:

$$v_i^{k+1} = W_{CPSO} * v_i^k + c_1old * rand_1*(p_{bi}^k - x_i^k) + c_2old * rand_2*(g_{bi}^k - x_i^k) \quad (23)$$

where W_{CPSO} in the $CPSO$ decreases and oscillates simultaneously from (0.9 to 0.4), but in the simple PSO and $MPSO$, W is linearly decreasing from (0.9 to 0.4). And the particle update your position is the same as in equations (16) and (20). Figure 1 shows the flowchart of CPSO algorithim.

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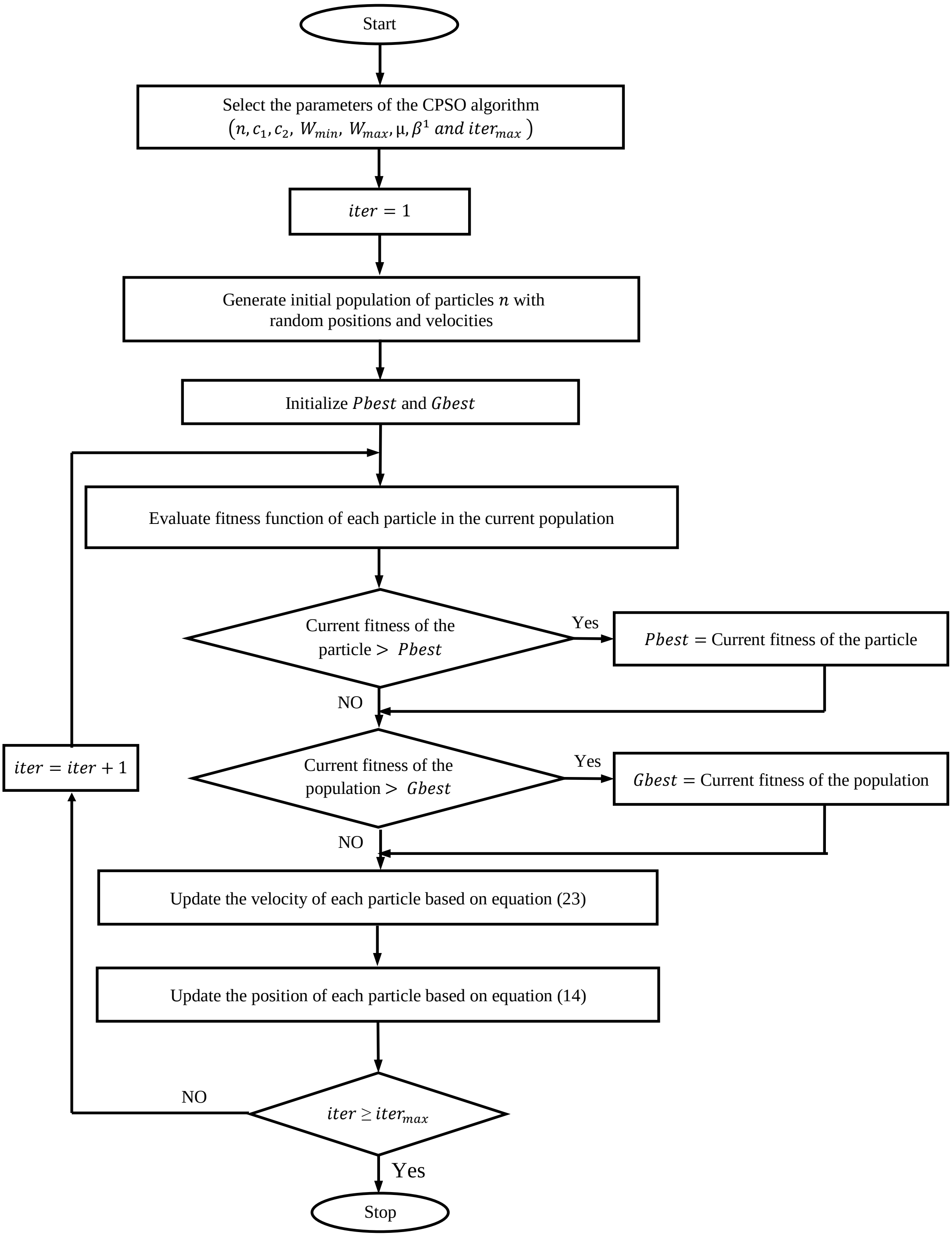

Figure 1. CPSO algorithm

CASE STUDY AND SIMULATION RESULTS

To assess the efficiency, accuracy and ability of the CPSO algorithm and also to discover the optimal solution for the reactive power optimization problem. Standard IEEE node−57 and node−118 systems are utilized to examine and test the proposed approach. PSO, MPSO and CPSO algorithms have been represented in MATLAB programing language.

IEEE− 57 node system

Bus, line, generator data and the bounds of generator reactive power in MVAR of standard IEEE-57 node systems are taken from reference [29]. The transformers tap (Tap) and generator voltages limits (V_G) and shunt capacitors (Q_C) bounds are shown in Table 1. This system contain 80 branches, 17 transformers tap ratio (Tap), 3 VAR sources (shunt capacitors

Q_C) and 7 generators node (V_G). This means the system is provided with 20 discrete and 7 continuous control variables that utilized for controlling the system. Therefore, the system has 27 dimension search spaces that listed in Table 2. Simulation results of standard IEEE-57 node system were tested through a series of comparisons among PSO, MPSO and CPSO with other optimization methods such as (SOA and OSGA) algorithms, which are given below in Table 2. From this table it is clear that the reduction in P_{loss} from the base case is **15.7%** at OGSA, **12.9%** at SOA, **14.3%** at PSO, **15.4%** at MPSO and **17.9%** at CPSO. Figures 2, 3 and 4 show the convergence for standard IEEE− 57 node system, and Figure 4 shows the voltage profile for this system with PSO, MPSO and CPSO algorithms. From Figure 4 it is clear that the voltage average at initial is about **0.992,** at PSO is about **1.014,** at MPSO is about **1.024,** and at CPSO is about **1.036**.

Table 1. Control Variables Settings

Power System Type	Independent Variables	Minimum (p.u.)	Maximum (p.u.)
IEEE BUS− 57	Generator node (V_G)	0.95	1.1
	Transformer tap (Tap)	0.9	1.1
	VAR source (Q_C)	0	0.20

Table 2. Simulation Results of IEEE-57 Node System

Control Variables	Base case	OGSA [31]	SOA [30]	PSO	MPSO	CPSO
V_G 1 (p.u.)	1.040	1.060	1.060	1.083	1.093	1.100
V_G 2 (p.u.)	1.010	1.059	1.058	1.071	1.086	1.095
V_G 3 (p.u.)	0.985	1.049	1.043	1.055	1.056	1.073
V_G 6 (p.u.)	0.980	1.043	1.035	1.036	1.038	1.062
V_G 8 (p.u.)	1.005	1.060	1.054	1.059	1.066	1.080
V_G 9 (p.u.)	0.980	1.045	1.036	1.048	1.054	1.064
V_G 12 (p.u.)	1.015	1.040	1.033	1.046	1.054	1.053
Tap 19 (p.u.)	0.970	0.900	1.000	0.987	0.975	0.982
Tap 20 (p.u.)	0.978	0.994	0.960	0.983	0.982	0.980
Tap 31 (p.u.)	1.043	0.900	1.010	0.981	0.975	0.995
Tap 35 (p.u.)	1.000	NR*	NR*	1.003	1.025	1.006
Tap 36 (p.u.)	1.000	NR*	NR*	0.985	1.002	1.002
Tap 37 (p.u.)	1.043	0.900	1.010	1.009	1.007	1.001
Tap 41 (p.u.)	0.967	0.911	0.970	1.007	0.994	1.004
Tap 46 (p.u.)	0.975	0.900	0.970	1.018	1.013	1.017
Tap 54 (p.u.)	0.955	0.900	0.900	0.986	0.988	0.986
Tap 58 (p.u.)	0.955	0.900	0.970	0.992	0.979	0.995
Tap 59 (p.u.)	0.900	1.046	0.950	0.990	0.983	0.976
Tap 65 (p.u.)	0.930	0.987	0.960	0.997	1.015	0.994
Tap 66 (p.u.)	0.895	0.963	0.920	0.984	0.975	0.968
Tap 71 (p.u.)	0.958	0.900	0.960	0.990	1.020	0.992
Tap 73 (p.u.)	0.958	0.900	1.000	0.988	1.001	0.981
Tap 76 (p.u.)	0.980	1.014	0.960	0.980	0.979	0.977
Tap 80 (p.u.)	0.940	0.983	0.970	1.017	1.002	1.012
Q_C 18 (p.u.)	0.1	0.068	0.099	0.131	0.179	0.109
Q_C 25 (p.u.)	0.059	0.059	0.059	0.144	0.176	0.138
Q_C 53 (p.u.)	0.063	0.063	0.062	0.162	0.141	0.113
P_G (MW)	1278.6	1274	1275	1274.8	1274.4	1273.8
Q_G (Mvar)	321.08	291.6	296.8	276.58	272.27	267.62
P_{loss} (MW)	**27.8**	**23.43**	**24.26**	**23.86**	**23.51**	**22.86**
P_{loss} Reduction %	**0**	**15.7**	**12.9**	**14.3**	**15.4**	**17.9**

NR*: means that the value was not reported in the literature.

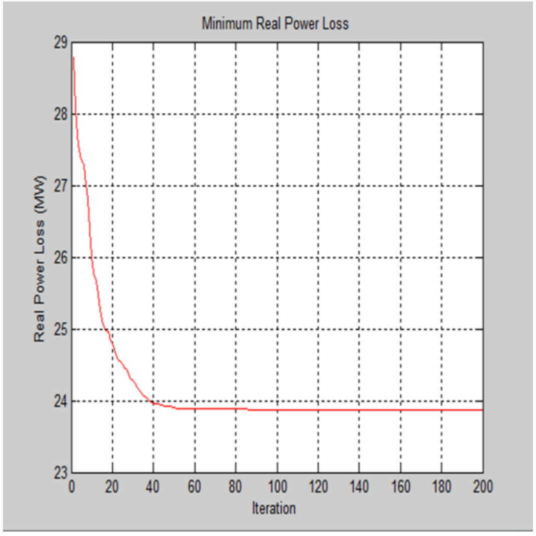

Figure 2. Convergence of IEEE−57 node system with PSO algorithm

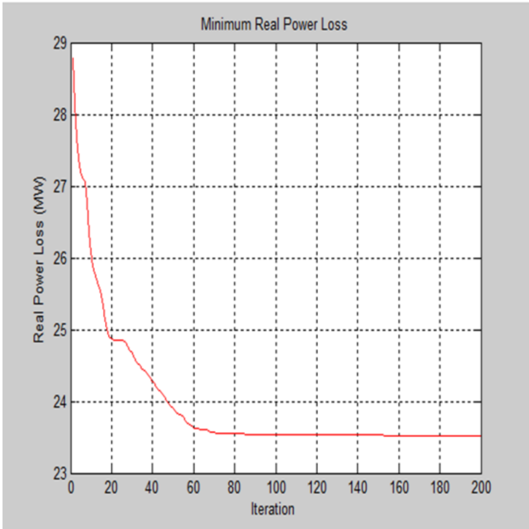

Figure 3. Convergence of IEEE−57 node system with MPSO algorithm

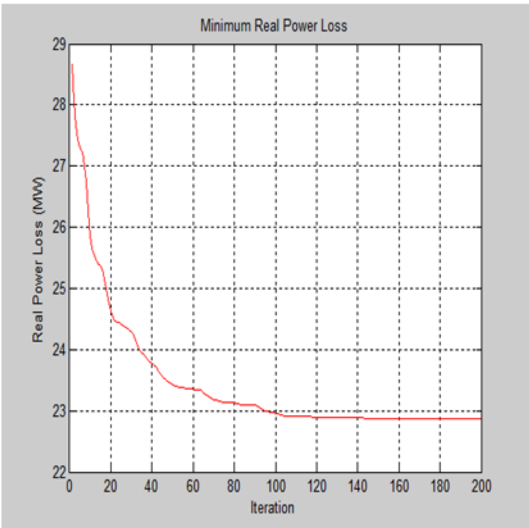

Figure 4. Convergence of IEEE−57 node system with CPSO algorithm

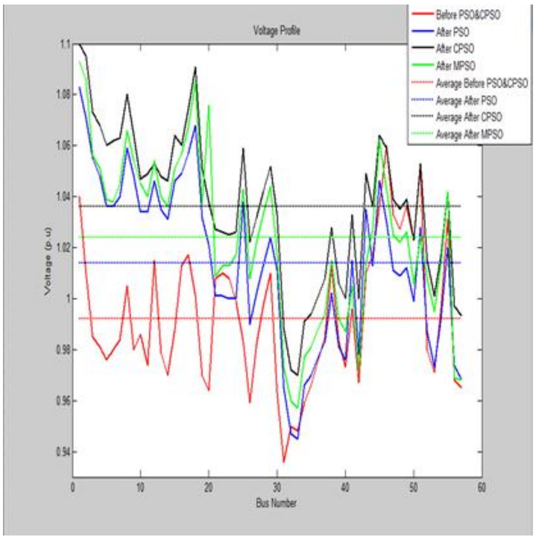

Figure 5. Voltage profile of IEEE−57 node system

IEEE− 118 node system

IEEE−118 node system is utilizing to test and exam the proposed approach in a large power system. Bus, line, generator data and the bounds of generator reactive power in MVAR of standard IEEE-57 node systems are taken from reference [32]. The transformers tap (Tap) and generator voltages limits (V_G) and shunt capacitors (Q_C) bounds are shown in Table 3. This system include 186 branches, 9 transformers tap ratio (Tap), 12 VAR sources (shunt capacitors Q_C) and 54 generators node (V_G). This means the system is provided with 21 discrete and 54 continuous control variables that utilized for controlling the system. Therefore, the system has 75 dimension search spaces that listed in Table 4. Simulation results of standard IEEE-118 node system were tested through a series of comparisons among PSO, MPSO and CPSO with other optimization methods such as (PSO and GSA) algorithms, which are given below in Table 4. From this table it is clear that the reduction in P_{loss} from the base case is **0.6%** at PSO [33], **3.8%** at GSA [33], **10.1%** at PSO, **11.8%** at MPSO and **15.2%** at CPSO. Figures 6, 7 and 8 show the convergence for standard IEEE−118 node system, and Figure 9 shows the voltage profile for this system with PSO, MPSO and CPSO algorithms. From Figure 9 it is clear that the voltage average at initial is about **0.986,** at PSO is about **1.024,** at MPSO is about **1.033,** and at CPSO is about **1.045**.

Table 3. Control Variables Settings

Power System Type	Independent Variables	Minimum (p.u.)	Maximum (p.u.)
IEEE BUS− 118	Generator node (V_G)	0.95	1.1
	Transformer tap (Tap)	0.9	1.1
	VAR source (Q_C)	0	0.20

Table 4. Simulation Results of IEEE-118 Node

Control Variables	Base case	PSO [33]	GSA [34]	PSO	MPSO	CPSO
V_G 1 (p.u.)	0.955	1.085	0.960	1.019	1.021	1.028
V_G 4 (p.u.)	0.998	1.042	0.962	1.038	1.044	1.048
V_G 6 (p.u.)	0.990	1.080	0.972	1.044	1.044	1.036
V_G 8 (p.u.)	1.015	0.968	1.057	1.039	1.063	1.047
V_G 10 (p.u.)	1.050	1.075	1.088	1.040	1.084	1.099
V_G 12 (p.u.)	0.990	1.022	0.963	1.029	1.032	1.033
V_G 15 (p.u.)	0.970	1.078	1.012	1.020	1.024	1.026
V_G 18 (p.u.)	0.973	1.049	1.006	1.016	1.042	1.034
V_G 19 (p.u.)	0.962	1.077	1.000	1.015	1.031	1.028
V_G 24 (p.u.)	0.992	1.082	1.010	1.033	1.058	1.047
V_G 25 (p.u.)	1.050	0.956	1.010	1.059	1.064	1.075
V_G 26 (p.u.)	1.015	1.080	1.040	1.049	1.033	1.091
V_G 27 (p.u.)	0.968	1.087	0.980	1.021	1.020	1.027
V_G31 (p.u.)	0.967	0.960	0.950	1.012	1.023	1.012
V_G 32 (p.u.)	0.963	1.100	0.955	1.018	1.023	1.021
V_G 34 (p.u.)	0.984	0.961	0.991	1.023	1.034	1.047
V_G 36 (p.u.)	0.980	1.036	1.009	1.014	1.035	1.046
V_G 40 (p.u.)	0.970	1.091	0.950	1.015	1.016	1.024
V_G 42 (p.u.)	0.985	0.970	0.950	1.015	1.019	1.029
V_G 46 (p.u.)	1.005	1.039	0.981	1.017	1.010	1.054
V_G 49 (p.u.)	1.025	1.083	1.044	1.030	1.045	1.069
V_G 54 (p.u.)	0.955	0.976	1.037	1.020	1.029	1.033
V_G 55 (p.u.)	0.952	1.010	0.990	1.017	1.031	1.030
V_G 56 (p.u.)	0.954	0.953	1.033	1.018	1.029	1.032
V_G 59 (p.u.)	0.985	0.967	1.009	1.042	1.052	1.062
V_G 61 (p.u.)	0.995	1.093	1.092	1.029	1.042	1.077
V_G 62 (p.u.)	0.998	1.097	1.039	1.029	1.029	1.072
V_G 65 (p.u.)	1.005	1.089	0.999	1.042	1.054	1.096
V_G 66 (p.u.)	1.050	1.086	1.035	1.054	1.056	1.051
V_G 69 (p.u.)	1.035	0.966	1.100	1.058	1.072	1.078
V_G 70 (p.u.)	0.984	1.078	1.099	1.031	1.040	1.043
V_G 72 (p.u.)	0.980	0.950	1.001	1.039	1.039	1.040
V_G 73 (p.u.)	0.991	0.972	1.011	1.015	1.028	1.039
V_G 74 (p.u.)	0.958	0.971	1.047	1.029	1.032	1.028
V_G 76 (p.u.)	0.943	0.960	1.021	1.021	1.005	1.026
V_G 77 (p.u.)	1.006	1.078	1.018	1.026	1.038	1.053
V_G 80 (p.u.)	1.040	1.078	1.046	1.038	1.049	1.067

Control Variables	**Base case**	**PSO [33]**	**GSA [34]**	**PSO**	**MPSO**	**CPSO**
V_G 85 (p.u.)	0.985	0.956	1.049	1.024	1.024	1.062
V_G 87 (p.u.)	1.015	0.964	1.042	1.022	1.019	1.025
V_G 89 (p.u.)	1.000	0.974	1.095	1.061	1.074	1.083
V_G 90 (p.u.)	1.005	1.024	1.041	1.032	1.045	1.046
V_G 91 (p.u.)	0.980	0.961	1.003	1.033	1.052	1.043
V_G 92 (p.u.)	0.990	0.956	1.001	1.038	1.058	1.062
V_G 99 (p.u.)	1.010	0.954	1.048	1.037	1.023	1.053
V_G 100 (p.u.)	1.017	0.958	1.033	1.037	1.049	1.060
V_G 103 (p.u.)	1.010	1.016	1.042	1.031	1.045	1.048
V_G 104 (p.u.)	0.971	1.099	1.018	1.031	1.035	1.038
V_G 105 (p.u.)	0.965	0.969	1.022	1.029	1.043	1.038
V_G 107 (p.u.)	0.952	0.965	1.034	1.008	1.023	1.024
V_G 110 (p.u.)	0.973	1.087	1.034	1.028	1.032	1.041
V_G 111 (p.u.)	0.980	1.037	1.042	1.039	1.035	1.049
V_G 112 (p.u.)	0.975	1.092	1.016	1.019	1.018	1.023
V_G 113 (p.u.)	0.993	1.075	1.018	1.027	1.043	1.039
V_G 116 (p.u.)	1.005	0.959	1.033	1.031	1.011	1.080
Tap 8 (p.u.)	0.985	1.011	1.065	0.994	0.999	0.981
Tap 32 (p.u.)	0.960	1.090	0.953	1.013	1.017	0.979
Tap 36 (p.u.)	0.960	1.003	0.932	0.997	0.994	1.007
Tap 51 (p.u.)	0.935	1.000	1.088	1.000	0.998	1.004
Tap 93 (p.u.)	0.960	1.008	1.057	0.997	1.000	0.994
Tap 95 (p.u.)	0.985	1.032	0.949	1.020	0.995	0.992
Tap 102 (p.u.)	0.935	0.944	0.997	1.004	1.024	0.983
Tap 107 (p.u.)	0.935	0.906	0.988	1.008	0.989	1.002
Tap 127 (p.u.)	0.935	0.967	0.980	1.009	1.010	1.003
Q_C 34 (p.u.)	0.140	0.093	0.074	0.048	0.049	0.120
Q_C 44 (p.u.)	0.100	0.093	0.060	0.026	0.026	0.131
Q_C 45 (p.u.)	0.100	0.086	0.033	0.197	0.196	0.161
Q_C 46 (p.u.)	0.100	0.089	0.065	0.118	0.117	0.034
Q_C 48 (p.u.)	0.150	0.118	0.044	0.056	0.056	0.047
Q_C 74 (p.u.)	0.120	0.046	0.097	0.120	0.120	0.112
Q_C 79 (p.u.)	0.200	0.105	0.014	0.140	0.139	0.150
Q_C 82 (p.u.)	0.200	0.164	0.174	0.180	0.180	0.190
Q_C 83 (p.u.)	0.100	0.096	0.042	0.166	0.166	0.163
Q_C 105 (p.u.)	0.200	0.089	0.120	0.190	0.189	0.026
Q_C 107 (p.u.)	0.060	0.050	0.022	0.129	0.128	0.077
Q_C 110 (p.u.)	0.060	0.055	0.029	0.014	0.014	0.137
P_G (MW)	4374.8	NR*	NR*	4361.4	4359.3	4354.7
Q_G (Mvar)	795.6	NR*	NR*	653.5	604.3	535.5
P_{loss} (MW)	**132.8**	**131.99**	**127.76**	**119.34**	**117.19**	**112.65**
P_{loss} Reduction %	**0**	**0.6**	**3.8**	**10.1**	**11.8**	**15.2**

NR*: means that the value was not reported in the literature.

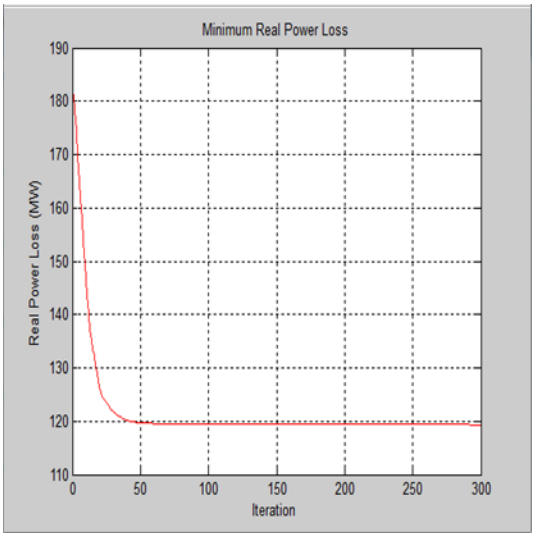

Figure 6. Convergence of IEEE−118 node system with PSO algorithm

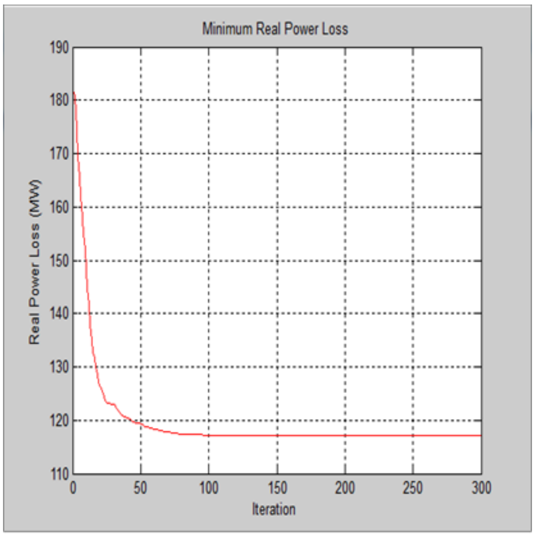

Figure 7. Convergence of IEEE−118 node system with MPSO algorithm

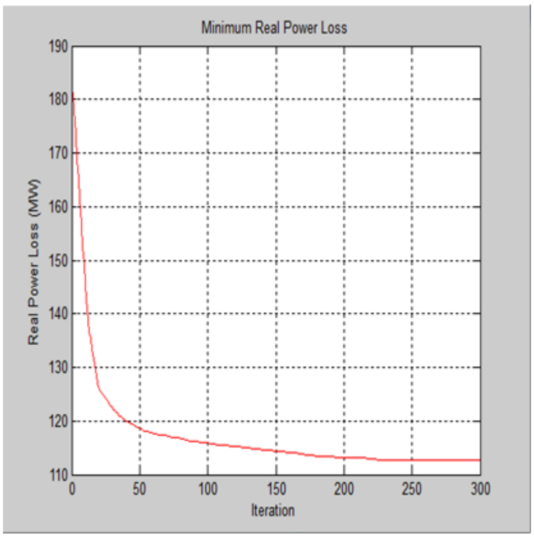

Figure 8. Convergence of IEEE−118 node system with CPSO algorithm

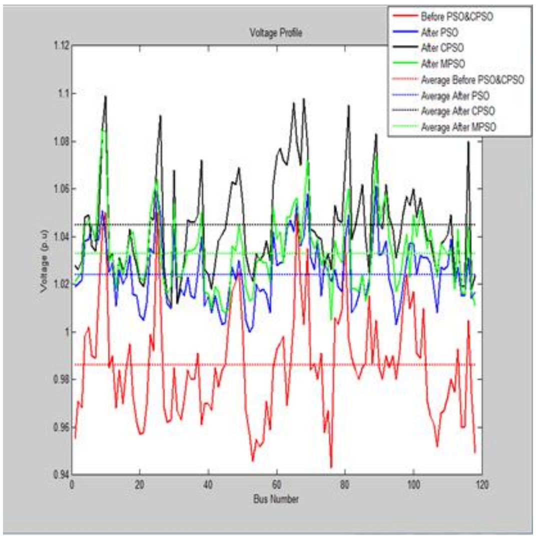

Figure 9. Voltage profile of IEEE−118 node system

CONCLUSION

In this study, three types of PSO algorithm are utilized for reactive power optimization problem. The objective function has been used to decrease power loss in the power system branches and voltage profile improvement. The efficiency and high quality of CPSO algorithm has been proved by examine on IEEE−57 node and −118 node systems. It is proved; the calculated results in CPSO algorithm are the better results. Therefore, CPSO provided the best technique to search for optimal solution that decreased the calculation time and rapiding convergence in both power loss minimization and voltage profile improvement if compared with the results obtained from using simple PSO, MPSO and other results that reported in the literature.

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