Research Journal of Applied Sciences, Engineering and Technology 15(8): 316-327, 2018
DOI:10.19026/rjaset.15.5917
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: March 22, 2018 Accepted: April 23, 2018 Published: August 15, 2018

Research Article

Modified Particle Swarm Optimization for Solution of Reactive Power Dispatch

[1]Ali Nasser Hussain, [2]Ali Abdulabbas Abdullah and [1]Omar Muhammed Neda
[1]Department of Electrical Power Engineering Techniques, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq
[2]AL-Najaf Engineering Technical College, AL-Furat AL-Awsat Technical University, AL-Najaf, Iraq

Abstract: Reactive Power Dispatch (RPD) is a complex, non−continuous and it is famous and essential problem in the power system. The calculation of this problem is really part of optimal load flow calculations. In this study, two types of Particle Swarm Optimization (PSO) algorithm are utilize as an optimization tools to solve RPD problem in order to minimize real Power Loss (P_{Loss}) in the power system and keep voltage at all buses within acceptable limit. First type of PSO algorithm is Conventional PSO and the second type is utilize to improve the searching quality, also to decrease the time calculation and to enhance the convergence characteristic in the first type, it is called Modified PSO (MPSO). These types of PSO algorithm are tested on IEEE Node− 14, Node−30, Node−57 and Node−118 power systems to test their efficiency and ability in solving RPD problem in small and large power systems. The simulation results in four power systems show that the MPSO algorithm has a better performance in decreasing losses, decreasing time calculation and enhancement of voltage profile when compared to the Conventional PSO and other algorithms that reported in the literature.

Keywords: Conventional PSO, modified PSO, optimal load flow calculations, power loss, reactive power dispatch, voltage profile

INTRODUCTION

Reactive Power Dispatch (RPD) problem is played essential role in enhancing the work of power system. The main goals of RPD are to minimization the losses in branches and voltage profile enhancement. This idea is accomplished through a suitable tuning for reactive power devices like generator voltages (V_G), transformers ratio (Tap) and reactive power sources (capacitor Q_C /reactor X_L). While dealing with some equality and inequality constrains including load flow equations (Abido, 2006; Deeb and Shidepour, 1990; Durairaj *et al*., 2006).

RPD calculation is really a part of optimal load flow calculations. Carpentier was introduced the Optimal Power Flow (OPF) calculations in year 1962s (Carpentier, 1962). Then, several researchers have been working on solving OPF problem by utilizing multi methods for example recursive quadratic, linear and nonlinear programing, interior point method and so on (Habiabollahzadeh *et al*., 1989; Aoki *et al*., 1987; Yan and Quintana, 1999; Momoh and Zhu, 1999).

Several classical techniques have been presented for solution RPD like linear programming, nonlinear programing, quadratic programming, interior point technique, newton approach and so on (Kirschen and Van Meeteren, 1988; Lee *et al*., 1985; Quintana and Santos-Nieto, 1989; Nanda *et al*., 1989; Liu *et al*., 1992; Granville, 1994; Yan *et al*., 2006). These classical techniques have many restrictions such as, want of continuous as well as differentiable objective functions, slip to local optima and complexity in dealing with a very big number of variables (Bakare *et al*., 2005). Thus, it becomes necessary to improve optimization methods which are able to avoiding these disadvantages.

To avoid these disadvantages, several optimization methods which have flexibility and ability for dealing with complex problem for example, evolutionary programming (Wu and Ma, 1995; Liang *et al*., 2006), simple, improve and adaptive Genetic Algorithm (GA) (Iba, 1994; Durairaj *et al*., 2006; Devaraj, 2007; Wu *et al*., 1998) evolutionary strategies (Bhagwan Das and Patvardhan, 2003), Differential Evolution (DE) (Abou El Ela *et al*., 2011; Liang *et al*., 2007; Varadarajan and Swarup, 2008), Harmony Search (HS) (Khazali and Kalantar, 2011), Particle Swarm Optimization (PSO) (Yoshida *et al*., 2000), Seeker Optimization Algorithm (SOA) (Dai *et al*., 2009), Biogeography Based Optimization (BBO) (Bhattacharya and Chattopadhyay, 2010), Gravitational Search Algorithm (GSA) (Duman *et al*., 2012). These methods have presented high efficiency in solving RPD problem.

Corresponding Author: Ali Nasser Hussain, Department of Electrical Power Engineering Techniques, Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq, Tel.: +964-07725297333

Lateef *et al*., presented Fully Informed PSO (FIPSO) to solution of RPD problem. The researchers applied this approach on standard IEEE 6−node, 30−node and 118−node systems to decrease the loss (Tehzeeb-Ul-Hassan *et al*., 2012). Junghare *et al*. presented Dynamic PSO (DPSO) on RPD problems to reduce the branch loss for 6 − node system (Badar *et al*., 2012). Roben *et al*. developed a new DE algorithm to solution of RPD problem. The researchers in this study work on the implications of steady state voltage stability (Ramirez *et al*., 2011). Chang *et al*., presented improved Hybrid DE (HDE) for the solution of RPD problem. The researchers used HDE on IEEE 30−node system (Yang *et al*., 2012). Baskar *et al*., adopted a Modified NSGA−II (MNSGA − II) to deal with multi objective RPD problem for system voltage stability as well as reducing active power loss (Jeyadevi *et al*., 2011).

Mehdinejad *et al*. (2016) investigated the improvement hybrid PSO and imperialist competitive (PSO − ICA) in order to solution the RPD problem in power systems. Standard IEEE −57 node and 118 node systems are utilized for solution of this problem with two objectives for decreasing of line loss and Total Voltage Deviation (TVD) (Mehdinejad *et al*., 2016). Habibi *et al*. proposed a new hybrid algorithm to manage discrete and continuous variables for solving RPD problem (Ghasemi *et al*., 2014).

In this study utilize Conventional PSO and MPSO algorithms for solving RPD problem. The great aim in this study is to enhance the performance, quality and convergence characteristic of Conventional PSO. The main objective is to decrease power loss through a suitable adjustment of control variables (V_G, Tap and Q_C) while dealing with number of inequality and equality constrains. IEEE Nodes - 14, - 30, - 57 and - 118 are utilizing as a test systems so as to test the efficiency and flexibility of MPSO for solving this problem. The simulation results prove that the results obtained in MPSO is better in decreasing line power loss as well as enhancement of voltage profile for the system compared to those in Conventional PSO and other reported papers.

MATERIALS AND METHODS

Problem formulation: The main goal of the objective function of RPD problem is to decrease Power Losses (P_{Loss}) of the system through proper adjustment of control parameters and at the same time dealing with equality and unequal constrains and the equation of P_{Loss} can be expressed as (Rajan and Malakar, 2015):

$$\text{Min } P_{Loss} = \sum_{K=1}^{Ntl} G_K({V_i}^2 + {V_j}^2 - 2V_iV_i\cos(\phi_i - \phi_j) \quad (1)$$

From Eq. (1),

Ntl : The number of branches
P_{loss} : The active power losses
G_K : The conductance of line K
V_i : The voltage value at i −node
V_j : The voltage value at j −node
ϕ_i, ϕ_j : The difference angles voltage at node i and j

Constrains: They are two types of constrains in RPD problem as follows:

Equality constrains: These constrains are the equations of the Power Flow and defined by the following equation (Rajan and Malakar, 2015):

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j(G_{ij}cos(\phi_{ij}) + B_{ij}sin(\phi_{ij}) = 0 \quad (2)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j(G_{ij}sin(\phi_{ij}) - B_{ij}cos(\phi_{ij}) = 0 \quad (3)$$

From Eq. (2) and (3),
NB : The total number of nodes in the system
P_{Gi} : The output real power
Q_{Gi} : The output reactive power of generator at node i
P_{Di} : The load active power
Q_{Di} : The load reactive power at node i
G_{ij} : The mutual conductance among i node and $j$node
B_{ij} : The mutual susceptance among i node and $j$node
V_i : The voltage value in i node
V_j : The voltage value in j node
ϕ_{ij} : The voltage angle variation in node i and j

Inequality constrains: These constrains including independent variables (control variables) like generator voltages (V_G), Transformers ratio (Tap) and switch-able VAR sources (Q_C). Also including state variables such as voltages at load node (V_L) and output reactive power of the generator (Q_G) as follows (Rajan and Malakar, 2015):

Control variables:

$$V_{Gi-min} \le V_{Gi} \le V_{Gi-max} \; i = 1, \ldots, N_G \quad (4)$$

$$Tap_{\,i-min} \le Tap_{\,i} \le Tap_{\,i-max} \; i = 1, \ldots, N_T \quad (5)$$

$$Q_{Ci-min} \le Q_{Ci} \le Q_{Ci-max} \; i = 1, \ldots, N_T \quad (6)$$

State variables:

$$V_{Li-min} \le V_{Li} \le V_{Li-max} \; i = 1, \ldots, N_{PQ} \quad (7)$$

$$Q_{Gi-min} \leq Q_{Gi} \leq Q_{Gi-max} \; i = 1, \ldots, N_G \quad (8)$$

In this study, state variables (V_L, Q_G) can be incorporated with Eq. (1) as a quadratic penalty terms. Thus, Eq. (1) can be written as shown in Eq. (9), (Rajan and Malakar, 2015):

$$min\ F = P_{loss} + \lambda_V \sum_{i=1}^{NL} (v_{Li} - v_{Li}{}^{lim})^2 + \lambda_Q \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}{}^{lim})^2 \quad (9)$$

In the above equation, λ_V and λ_Q are penalty terms and 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 Eq. (1).

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

$$V_{av} = \frac{\sum_{i=1}^{Nn} V_i}{N_n} \quad (10)$$

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

Conventional PSO algorithm: This technique is fast, robust, simple, high accuracy and requires less time calculation. Eberhart and Kennedy were first introduced PSO in year 1995 (Kennedy and Eberhart, 1995). PSO is a kind of big group of swarm intelligence techniques that emerged to be a favorable tool for dealing with optimization problems. It is a type of stochastic optimization technique; it has behavior like the behavior of flock school fish or swarms of birds in order to search for food. Each agent have local best position discover by the agent itself (P_{best}), as well as, the best position discovered between all agents in the population (P_{best}) is stored in a memory called (G_{best}). The (P_{best}) and (G_{best}) values are change at every iteration in PSO algorithm. Then, the agents change their speed and position by utilizing Eq. (11) and Eq. (12) (Vlachogiannis and Lee, 2006):

$$v_i{}^{k+1} = K*[w * v_i{}^k + c_1\text{old} * rand_1*(P_{bi}{}^k - x_i{}^k) + c_2\text{old}*rand_2*(G_{bi}{}^k - x_i{}^k)] \quad (11)$$

$$x_i{}^{k+1} = x_i{}^k + v_i{}^{k+1} \quad (12)$$

From the above equations:

v	: The velocity of agent
W	: The inertia weight
c_1 old, c_2 old	: The old constant learning factors between [0-2.5]
$rand_1, rand_2$	: The uniformly distributed positive number within limit $[0-1]$
P_{bi}	: The best position of agent
G_{bi}	: The global best position of agent
X_i	: The position of agent
K	: The constriction factor and it is utilized so as to guarantee the convergence of the algorithm and it can be expressed as (Eberhart and Shi, 2000):

$$K = \frac{2}{\left|2 - \phi - \sqrt{\phi^2 - 4\phi}\right|}, \phi = C_1 + C_2, \phi \geq 4 \quad (13)$$

In this study, (W) given in (11), 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 by utilizing Eq. (14):

$$W = W_{max} - \frac{W_{max} - W_{min}}{max_{iteration}} * iter \quad (14)$$

From the above equation:

W_{max}	: The max inertia
W_{min}	: The min inertia
$iter$	: The present iteration
$max_{iteration}$	: The max iterations

MPSO Algorithm: This algorithm is utilize so as to enhance the quality and the performance of Conventional PSO, so as to get best convergence characteristic, lesser time in calculation and solution is nearby to the optimal solution than Conventional PSO. In this algorithm, agents move to be nearest to the better position and discover the global minimum point (Niknam *et al.*, 2011). The worse implication is ignored but the best one is kept and recorded as the optimal implication unless a best one is achieved and is defined by P_{best}. As well as the best position among all the swarm initiate is estimated by G_{best}. The equations for the MPSO can be expressed as in Eq. (15) to (18):

$$v_i{}^{k+1} = w * v_i{}^k + c_1\text{new} * rand_1*(P_{bi}{}^k - x_i{}^k) + c_2\text{new}*rand_2*(G_{bi}{}^k - x_i{}^k) \quad (15)$$

$$x_i{}^{k+1} = x_i{}^k + v_i{}^{k+1} \quad (16)$$

$$c_1\text{new} = rand() \quad (17)$$

$$c_2\text{new} = rand() \quad (18)$$

The learning factors ($c_1$old and $c_2$old) given in Eq. (11) are modified to a random values ($c_1$new and $c_2$new) given in Eq. (15) within range [0,1] instead of constant value (c_1 old and c_2 old) given in PSO. When using $c_1$new and $c_2$new in MPSO raises the ability of Conventional PSO to discover the optimal solution faster than utilize (c_1 old and c_2 old) constant values given in Conventional PSO.

Representation of MPSO For Solving RPD: The MPSO algorithm has (7) steps are given as:

Step 1: Among minimum and maximum limits, are generated particles stochastic.
Step 2: Assign the initial particles for the local best value P_{best}.
Step 3: Calculate objective function related to local P_{best} and global G_{best} position.
Step 4: Update the x_i^{k+1} and v_i^{k+1} using Eq. (15) and (16) for all particles.
Step 5: Comparison an objective function for each agent based on its local best value P_{best} if it is bigger than P_{best} set present value as local best P_{best} and locate it as a present location in the search problem.
Step 6: According to the values of objective function, calculate the $min\ P_{best}$ and set as global G_{best}.
Step 7: The steps are repeated from step (4) to step (6) until max iteration.

RESULTS AND DISCUSSION

Conventional PSO and MPSO methods evaluated and tested on IEEE node−14, 30, 57 and 118 systems for solving RPD. The two PSO algorithms and other algorithms that reported in the literature have been implemented in MATLAB program and the number of particles and maximum iterations in this study are 50 and 200, respectively for the four test systems.

IEEE 14-Node system: This system consisting of 20 branches, 5 generators at (nodes 1, 2, 3, 6 and 8), 3 transformers are placed in (branches 8, 9 and 10) and one reactive power source compensation in (bus 9). Bus data, branch data, generator data and other operating data are given in reference (Pandya and Roy, 2015). The constrains of control variables are given in Table 1 and the constrains (Max, Min) of reactive power output (Q_G) of generators are given in Table 2 (Pandya and Roy, 2015). This system including 5 generator voltages (V_G), 3 transformers ratio (Tap) and 1 reactive power (VAR) compensation (Q_c), so this system has 9 dimensions of search space as given in Table 3. The simulation results for the presented algorithms is given also in Table 3 and compared with EP and SARGA algorithms (Subbaraj and Rajnarayan, 2009). The reduction in P_{Loss} is 9.2% at MPSO, 9.1% at PSO, 1.5% at EP and 2.5% at SARGA algorithms. Figure 1 and 2 show the convergence at 200 iteration and from these Figures it is clearly that the convergence characteristic of MPSO is better and effective for minimizing loss

Table 1: Constrains of control variables

Power system type	Independent variables	Min. (p.u.)	Max. (p.u.)
IEEEbus−14	Generator voltage (V_G)	0.95	1.1
	Transformer tap (OLTC)	0.9	1.1
	VAR source (Q_C)	0	0.20

Table 2: Constrains (Max, Min) of reactive power output (Q_G) of generators

Power system type	Generator variables	Q_{Min} (p.u.)	Q_{Max} (p.u.)
IEEEbus−14	1	0	10
	2	-40	50
	3	0	40
	6	-6	24
	8	-6	24

Table 3: Simulation results of IEEE Node−14 system

Control variables	Base case	MPSO	PSO	EP	SARGA
V_{G-1}	1.060	1.100	1.100	NR*	NR*
V_{G-2}	1.045	1.085	1.086	1.029	1.060
V_{G-3}	1.010	1.055	1.056	1.016	1.036
V_{G-6}	1.070	1.069	1.067	1.097	1.099
V_{G-8}	1.090	1.074	1.060	1.053	1.078
Tap_8	0.978	1.018	1.019	1.04	0.95
Tap_9	0.969	0.975	0.988	0.94	0.95
Tap_{10}	0.932	1.024	1.008	1.03	0.96
Q_{C-9}	0.19	14.64	0.185	0.18	0.06
P_G (MW)	272.39	271.32	271.32	NR*	NR*
Q_G (Mvar)	82.44	75.79	76.79	NR*	NR*
Reduction in P_{Loss} (%)	0	9.2	9.1	1.5	2.5
Total P_{Loss} (Mw)	13.550	12.293	12.315	13.346	13.216

NR* means not reported.

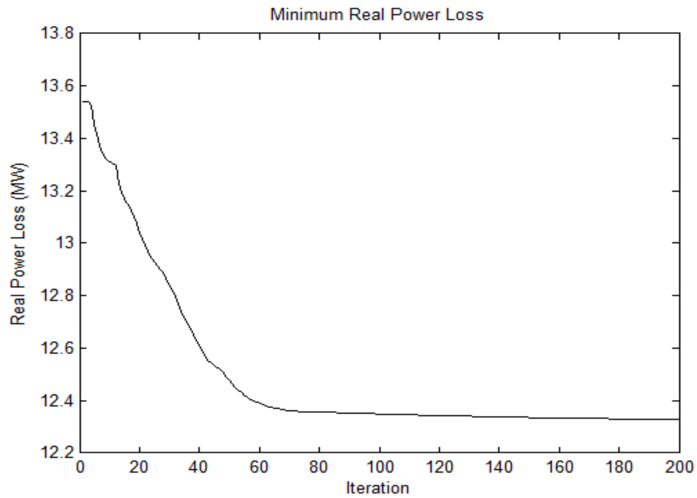

Fig. 1: Convergence for IEEE 14 node power system with conventional PSO algorithm

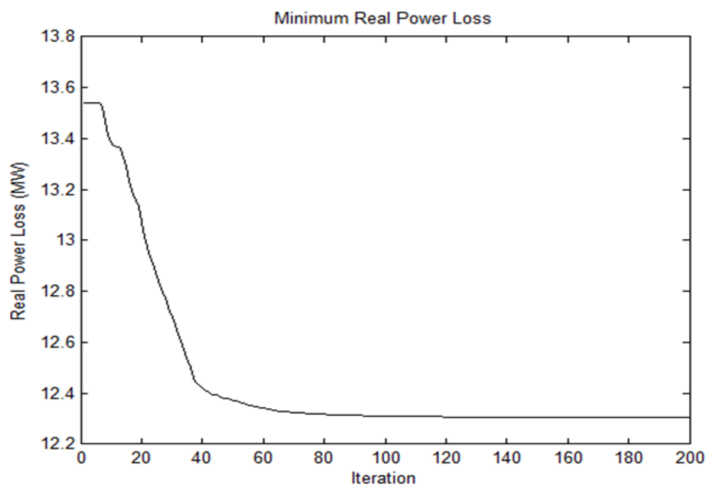

Fig. 2: Convergence for IEEE 14 node power system with MPSO algorithm

than Conventional PSO algorithm. The average voltage at initial is 1.048, at PSO is 1.059 and at MPSO is 1.081.

IEEE 30-node system: This system containing of 41 branches, 6 generators at (nodes 1, 2, 5, 8, 11 and 13), 4 transformers at (branches 11, 12, 15 and 36) and 2 reactive power source at (nodes 10 and 24). Bus data, branch data, generator data and other operating data in reference (Pandya and Roy, 2015). Bounds of independent (control) variables are written in Table 4 and constrains of reactive power output for generators (Q_G) are given in Table 5 (Pandya and Roy, 2015). This system has 12 independent variables (control variables), 6 generator voltages (V_G), 4 transformers ratio (Tap) and 2 reactive power compensation (capacitor banks)

Table 4: Constrains of independent (control) variables

Power system type	Independent variables	Min. (p.u.)	Max. (p.u.)
IEEEbus−30	Generator voltage (V_G)	0.95	1.1
	Transformer position (OLTC)	0.9	1.1
	VAR source (Q_C)	0	0.20

Table 5: Constrains of reactive power output for generators (Q_G)

Power system type	Generator variable	Q_{Min}	Q_{Max}
IEEEbus−30	1	0	10
	2	-40	50
	5	-40	40
	8	-10	40
	11	-6	24
	13	-6	24

Table 6: Simulation results of IEEE− 30 Node system

Control variables	Base case	MPSO	PSO	EP	SARGA
V_{G1}	1.060	1.101	1.100	NR*	NR*
V_{G2}	1.045	1.086	1.072	1.097	1.094
V_{G5}	1.010	1.047	1.038	1.049	1.053
V_{G8}	1.010	1.057	1.048	1.033	1.059
V_{G11}	1.082	1.048	1.058	1.092	1.099
V_{G13}	1.071	1.068	1.080	1.091	1.099
Tap_{11}	0.978	0.983	0.987	1.01	0.99
Tap_{12}	0.969	1.023	1.015	1.03	1.03
Tap_{15}	0.932	1.020	1.009	1.07	0.98
Tap_{36}	0.968	0.988	1.012	0.99	0.96
Q_{C10}	0.19	0.077	0.077	0.19	0.19
Q_{C24}	0.043	0.119	0.128	0.04	0.04
P_G (MW)	300.9	299.54	299.66	NR*	NR*
Q_G (Mvar)	133.9	130.83	130.94	NR*	NR*
Reduction in P_{Loss} (%)	0	8.4	7.4	6.6	8.3
Total P_{Loss} (Mw)	17.55	16.07	16.25	16.38	16.09

NR* means not reported.

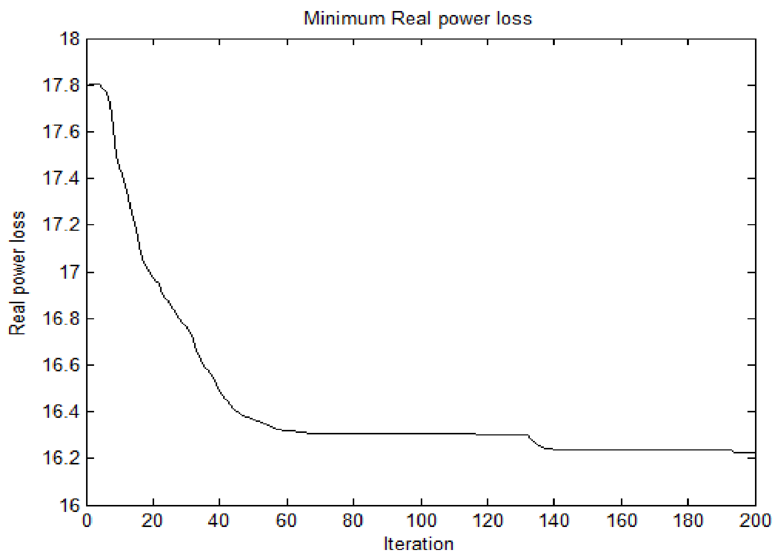

Fig. 3: Convergence of IEEE 30-node system with conventional PSO algorithm

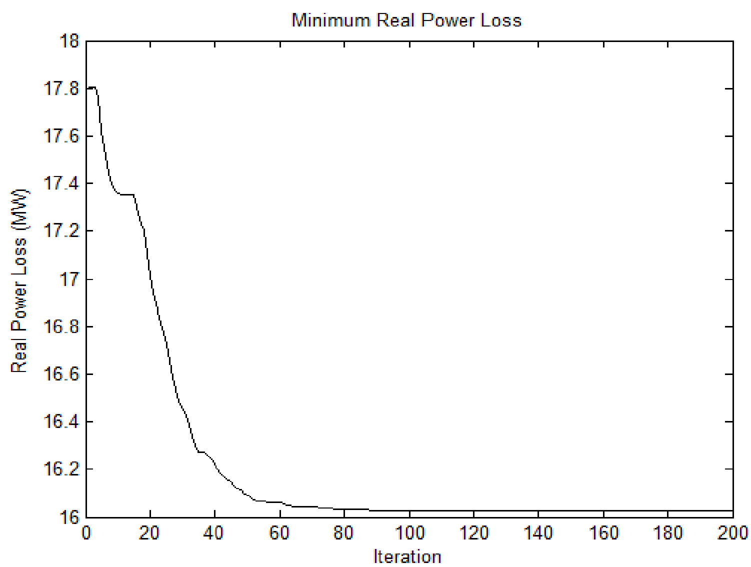

Fig. 4: Convergence of IEEE 30-node system with MPSO algorithm

VAR sources (Q_C) as given in Table 6. The simulation results for the presented algorithms are also given in Table 6 and also compared with EP and SARGA algorithms (Subbaraj and Rajnarayan, 2009). The reduction in P_L is 8.4% at MPSO, 7.4% at PSO, 6.6% at EP and 8.3% at SARGA algorithms. Figure 3 and 4 show the convergence at 200 iteration and from these Figures it is clearly that the convergence characteristic of MPSO is better and effective for minimizing loss than Conventional PSO algorithm. The average voltage at initial is 1.029, at PSO is 1.035 and at MPSO is 1.049.

IEEE 57-Node system: This standard system involves 80 branches, 7 generators, 17 transformers and 3 reactive power compensations. Bus, branch, generator and other operation data are given in reference (Pandya and Roy, 2015). The bounds of reactive power generation in (MVAR) are displayed in Table 7 (Pandya and Roy, 2015). This system includes 7 generator voltages node (V_G), 17 transformer ratio (Tap) and 3 switch-able (VAr) sources compensation as presented in Table 8, so this system has 27 independent control variables and the constrains of these variables are listed in Table 9. The simulation results are given in Table 8 that compared with CGA and AGA algorithms (Dai *et al*., 2009). The simulation results showed the best performance resulting from

Table 7: Constrains of reactive power generation

Power system type	Generator nodes	Q_{Min}	Q_{Max}
57 Bus	1	-140	200
	2	-17	50
	3	-10	60
	6	-8	25
	8	-140	200
	9	-3	9
	12	-150	155

Table 8: Simulation results of IEEE Node−57 systems

Control variables	Base case	MPSO	PSO	CGA	AGA
V_G 1	1.040	1.093	1.083	0.968	1.027
V_G 2	1.010	1.086	1.071	1.049	1.011
V_G 3	0.985	1.056	1.055	1.056	1.033
V_G 6	0.980	1.038	1.036	0.987	1.001
V_G 8	1.005	1.066	1.059	1.022	1.051
V_G 9	0.980	1.054	1.048	0.991	1.051
V_G 12	1.015	1.054	1.046	1.004	1.057
Tap 19	0.970	0.975	0.987	0.920	1.030
Tap 20	0.978	0.982	0.983	0.920	1.020
Tap 31	1.043	0.975	0.981	0.970	1.060
Tap 35	1.000	1.025	1.003	NR*	NR*
Tap 36	1.000	1.002	0.985	NR*	NR*
Tap 37	1.043	1.007	1.009	0.900	0.990
Tap 41	0.967	0.994	1.007	0.910	1.100
Tap 46	0.975	1.013	1.018	1.100	0.980
Tap 54	0.955	0.988	0.986	0.940	1.010
Tap 58	0.955	0.979	0.992	0.950	1.080
Tap 59	0.900	0.983	0.990	1.030	0.940
Tap 65	0.930	1.015	0.997	1.090	0.950
Tap 66	0.895	0.975	0.984	0.900	1.050
Tap 71	0.958	1.020	0.990	0.900	0.950
Tap 73	0.958	1.001	0.988	1.000	1.010
Tap 76	0.980	0.979	0.980	0.960	0.940
Tap 80	0.940	1.002	1.017	1.000	1.000
Q_C 18	0.1	0.179	0.131	0.084	0.016
Q_C 25	0.059	0.176	0.144	0.008	0.015
Q_C 53	0.063	0.141	0.162	0.053	0.038
P_G (MW)	1278.6	1274.4	1274.8	1276	1275
Q_G (Mvar)	321.08	272.27	276.58	309.1	304.4
Reduction in P_{Loss} (%)	0	15.4	14.1	9.2	11.6
Total P_{Loss} (Mw)	27.8	23.51	23.86	25.24	24.56

NR* means not reported.

Table 9: Independent (Control) variables settings

System type	Control variables	Min	Max
57 Bus	Generator voltage (V_G)	0.95	1.1
	Transformer Tap (Tap)	0.9	1.1
	VAR Source Compensation (Q_C)	0	0.20

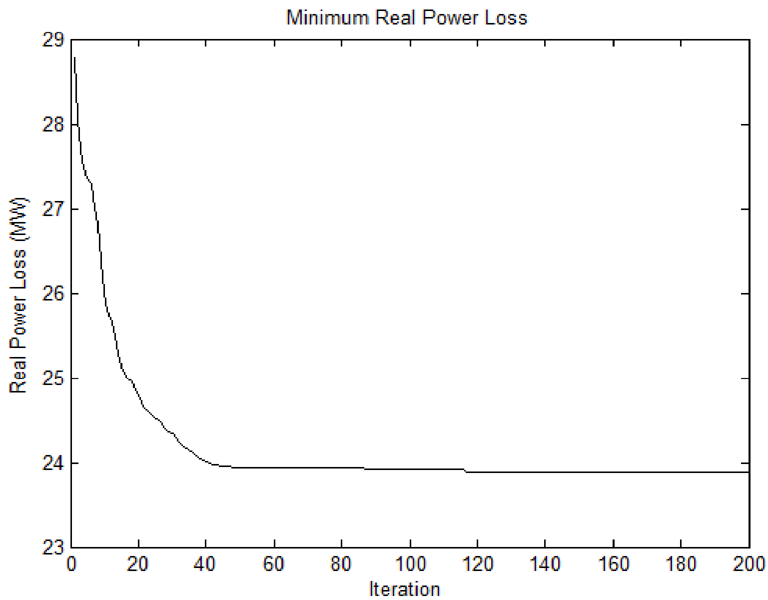

Fig. 5: Convergence for IEEE 57- node power system with conventional PSO algorithm

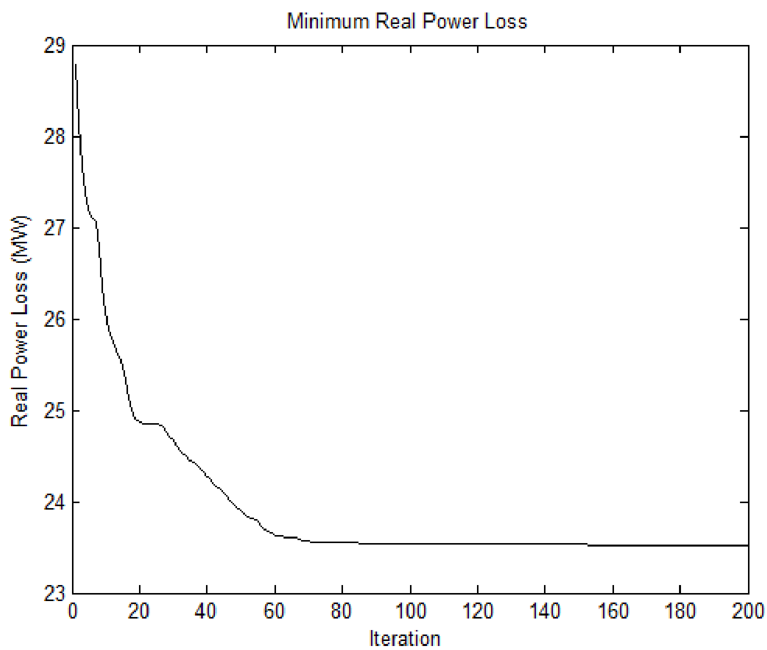

Fig. 6: Convergence for IEEE 57-node power system with MPSO algorithm

using MPSO algorithm over those resulting from using Conventional PSO and Other reported algorithms. The reduction in P_{Loss} is 15.4% at MPSO, 14.1% at PSO, 9.2% at CGA and 11.6% at AGA algorithms. Figure 5 and 6 show the convergence of Conventional PSO and MPSO algorithms also at 200 iterations and from these Figures are clearly that the convergence characteristic of MPSO is better and effective for minimizing loss than Conventional PSO algorithm. The average voltage at initial is 0.992, at PSO is 1.014 and at MPSO is 1.024.

IEEE 118-Node system: So as to test and evaluate the ability of the MPSO algorithm in handling large power system, IEEE node-118 is presented as a test system.

Table 10: Control variables constrains

System type	Variables	Min	Max
118 Bus	Generator voltage (V_G)	0.95	1.1
	Transformer Position (Tap)	0.9	1.1
	VAR Source Compensation (Q_C)	0	0.20

Table 11: Simulation results of IEEE Node−118 systems

Control variables	Base case	MPSO	PSO	PSO	CLPSO
V_G 1	0.955	1.021	1.019	1.085	1.033
V_G 4	0.998	1.044	1.038	1.042	1.055
V_G 6	0.990	1.044	1.044	1.080	0.975
V_G 8	1.015	1.063	1.039	0.968	0.966
V_G 10	1.050	1.084	1.040	1.075	0.981
V_G 12	0.990	1.032	1.029	1.022	1.009
V_G 15	0.970	1.024	1.020	1.078	0.978
V_G 18	0.973	1.042	1.016	1.049	1.079
V_G 19	0.962	1.031	1.015	1.077	1.080
V_G 24	0.992	1.058	1.033	1.082	1.028
V_G 25	1.050	1.064	1.059	0.956	1.030
V_G 26	1.015	1.033	1.049	1.080	0.987
V_G 27	0.968	1.020	1.021	1.087	1.015
V_G31	0.967	1.023	1.012	0.960	0.961
V_G 32	0.963	1.023	1.018	1.100	0.985
V_G 34	0.984	1.034	1.023	0.961	1.015
V_G 36	0.980	1.035	1.014	1.036	1.084
V_G 40	0.970	1.016	1.015	1.091	0.983
V_G 42	0.985	1.019	1.015	0.970	1.051
V_G 46	1.005	1.010	1.017	1.039	0.975
V_G 49	1.025	1.045	1.030	1.083	0.983
V_G 54	0.955	1.029	1.020	0.976	0.963
V_G 55	0.952	1.031	1.017	1.010	0.971
V_G56	0.954	1.029	1.018	0.953	1.025
V_G 59	0.985	1.052	1.042	0.967	1.000
V_G 61	0.995	1.042	1.029	1.093	1.077
V_G 62	0.998	1.029	1.029	1.097	1.048
V_G 65	1.005	1.054	1.042	1.089	0.968
V_G 66	1.050	1.056	1.054	1.086	0.964
V_G 69	1.035	1.072	1.058	0.966	0.957
V_G 70	0.984	1.040	1.031	1.078	0.976
V_G 72	0.980	1.039	1.039	0.950	1.024
V_G 73	0.991	1.028	1.015	0.972	0.965
V_G 74	0.958	1.032	1.029	0.971	1.073
V_G 76	0.943	1.005	1.021	0.960	1.030
V_G 77	1.006	1.038	1.026	1.078	1.027
V_G 80	1.040	1.049	1.038	1.078	0.985
V_G 85	0.985	1.024	1.024	0.956	0.983
V_G 87	1.015	1.019	1.022	0.964	1.088
V_G 89	1.000	1.074	1.061	0.974	0.989
V_G 90	1.005	1.045	1.032	1.024	0.990
V_G 91	0.980	1.052	1.033	0.961	1.028
V_G 92	0.990	1.058	1.038	0.956	0.976
V_G 99	1.010	1.023	1.037	0.954	1.088
V_G 100	1.017	1.049	1.037	0.958	0.961
V_G 103	1.010	1.045	1.031	1.016	0.961
V_G 104	0.971	1.035	1.031	1.099	1.012
V_G 105	0.965	1.043	1.029	0.969	1.068
V_G 107	0.952	1.023	1.008	0.965	0.976
V_G 110	0.973	1.032	1.028	1.087	1.041
V_G 111	0.980	1.035	1.039	1.037	0.979
V_G 112	0.975	1.018	1.019	1.092	0.976
V_G 113	0.993	1.043	1.027	1.075	0.972
V_G 116	1.005	1.011	1.031	0.959	1.033
Tap 8	0.985	0.999	0.994	1.011	1.004
Tap 32	0.960	1.017	1.013	1.090	1.060
Tap 36	0.960	0.994	0.997	1.003	1.000
Tap 51	0.935	0.998	1.000	1.000	1.000
Tap 93	0.960	1.000	0.997	1.008	0.992
Tap 95	0.985	0.995	1.020	1.032	1.007
Tap 102	0.935	1.024	1.004	0.944	1.061
Tap 107	0.935	0.989	1.008	0.906	0.930
Tap 127	0.935	1.010	1.009	0.967	0.957
Q_C 34	0.140	0.049	0.048	0.093	0.117
Q_C 44	0.100	0.026	0.026	0.093	0.098
Q_C 45	0.100	0.196	0.197	0.086	0.094
Q_C 46	0.100	0.117	0.118	0.089	0.026
Q_C 48	0.150	0.056	0.056	0.118	0.028
Q_C 74	0.120	0.120	0.120	0.046	0.005

Table 11: Continue

Control variables	Base case	MPSO	PSO	PSO	CLPSO
Q_C 79	0.200	0.139	0.140	0.105	0. 148
Q_C 82	0.200	0.180	0.180	0.164	0.194
Q_C 83	0.100	0.166	0.166	0.096	0.069
Q_C 105	0.200	0.189	0.190	0.089	0.090
Q_C 107	0.060	0.128	0.129	0.050	0.049
Q_C 110	0.060	0.014	0.014	0.055	0.022
$P_{G(MW)}$	4374.8	4359.3	4361.4	NR*	NR*
$Q_{G(MVAR)}$	795.6	604.3	653.5	NR*	NR*
Reduction in P_{LOSS} (%)	0	11.7	10.1	0.6	1.3
Total P_{LOSS} (Mw)	132.8	117.19	119.34	131.99	130.96

NR* means not reported.

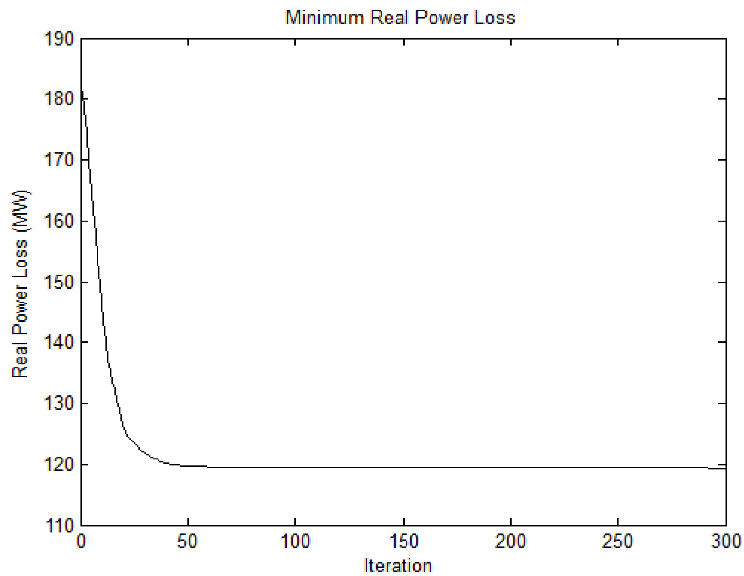

Fig. 7: Convergence of IEEE 118-node system with conventional PSO algorithm

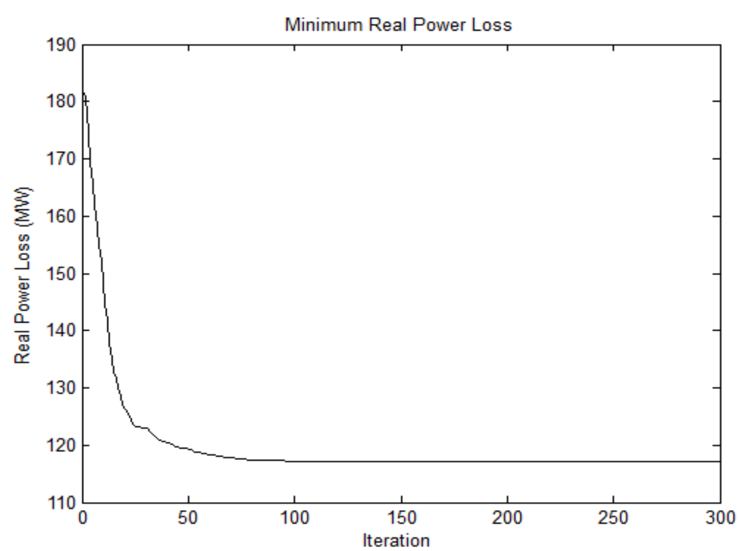

Fig. 8: Convergence of IEEE 118-node system with MPSO algorithm

Bus, generator, branch, the limits of reactive power generation output and other operating data are given in reference (Vlachogiannis and Lee, 2006). This system involves of 54 generators, 9 transformers and 12 banks of capacitors. The upper (max.) and lower (min.) bounds of transformer tap, reactive power compensation and generator nodes of independent control variables are listed in Table 10. In this system, the total numbers of independent control variables are 75 numbers, i.e., 54 generator voltages (V_G), 9 transformer ratios (Tap) and 12 injected VAR source from capacitor banks (Q_C) as presented in the simulation results Table 11. The simulation results for this case are given in Table 11 and compared with Conventional PSO and other algorithms that reported in the literature (Mahadevan and Kannan, 2010). From these results indicate that MPSO has high ability in solving RPD problem than other methods in this test. The reduction in P_{Loss} is 8.7% at MPSO, 7.4% at PSO, 6.6% at EP and 8.3% at SARGA algorithms. Figure 7 and 8 show the convergence of Conventional PSO and MPSO at 300 iterations and from these Figures it is clearly that the convergence characteristic of MPSO is best in minimizing loss than Conventional PSO algorithm. The average voltage at initial is 0.986, at PSO is 1.024 and at MPSO is 1.033.

CONCLUSION

In this study, in order to enhance the performance, quality and to avoid premature convergence of Convrntional PSO algorithm, MPSO algorithm is utilized for solving RPD problem. The two algorithims are presented on IEEE Node−14, −30, −57 and −118systems. From the simulation results, it is prove that MPSO algorithm is best in convergence speed characterastic to obtain optimal solutions that decreased the power loss as well as voltage profile improvement of the system and also the reduction in P_L is more than Conventional PSO and other algorithms that reported in the litreture such as, EP, SARGA algorithms at IEEE Node−14, −30, CGA, AGA algorithms at IEEE Node −57, PSO and CLPSO algorithms at at IEEE Node −118 in all presented test systems in this study. In addition, the simulation results proved that MPSO algorithm able to obtain best quality−solutions in lesser time than Conventional PSO for all presented systems for solving RPD and other complex problem in power system.

REFERENCES

Abido, M.A., 2006. Multiobjective optimal VAR dispatch using strength Pareto evolutionary algorithm. Proceeding of the 2006 IEEE Congress on Evolutionary Computation (CEC), pp: 730-736.

Abou El Ela, A.A., M.A. Abido and S.R. Spea, 2011. Differential evolution algorithm for optimal reactive power dispatch. Electr. Power Syst. Res., 81(2): 458-464.

Aoki, K., A. Nishikori and R.T. Yokoyama, 1987. Constrained load flow using recursive quadratic programming. IEEE T. Power Syst., 2(1): 8-16.

Badar, A.Q.H., B.S. Umre and A.S. Junghare, 2012. Reactive power control using dynamic particle swarm optimization for real power loss minimization. Int. J. Elec. Power, 41: 133-136.

Bakare, G.A., G.K. Venayagamoorthy and U.O. Aliyu, 2005. Reactive power and voltage control of the Nigerian grid system using micro-genetic algorithm. Proceeding of IEEE Power and Engineering Society General Meeting, pp: 1916-1922.

Bhagwan Das, D. and C. Patvardhan, 2003. A new hybrid evolutionary strategy for reactive power dispatch. Electr. Power Syst. Res., 65(2): 83-90.

Bhattacharya, A. and P.K. Chattopadhyay, 2010. Solution of optimal reactive power flow using biogeography-based optimization. Int. J. Electr. Electron. Eng., 4(3): 621-629.

Carpentier, J., 1962. Contribution to the economic dispatch problem. Bull. Soc. Fr. Electr., 3(8): 431-447.

Dai, C., W. Chen, Y. Zhu and X. Zhang, 2009. Seeker optimization algorithm for optimal reactive power dispatch. IEEE T. Power Syst., 24(3): 1218-1231.

Deeb, N. and S.M. Shaidepour, 1990. Linear reactive power optimization in a large power network using the decomposition approach. IEEE T. Power Syst., 5(2): 428-435.

Devaraj, D., 2007. Improved genetic algorithm for multi-objective reactive power dispatch problem. Eur. T. Electr. Power., 17(6): 569-581.

Duman, S., Y. Sonmez, U. Guvenc and N. Yorukeren, 2012. Optimal reactive power dispatch using a gravitational search algorithm. IET Gener. Transm. Dis., 6(6): 563-576.

Durairaj, S., D. Devaraj and P.S. Kannan, 2006. Genetic algorithm applications to optimal reactive power dispatch with voltage stability enhancement. J. Inst. Eng. (India): Electr. Eng. Div., 87: 42-47.

Eberhart, R.C. and Y. Shi, 2000. Comparing inertia weights and constriction factors in particle swarm optimization. Proceeding of the 2000 Congress on Evolutionary Computation, (CEC00). La Jolla, CA, USA, July 16-19, pp: 84-88.

Ghasemi, M., S. Ghavidel, M.M. Ghanbarian and A. Habibi, 2014. A new hybrid algorithm for optimal reactive power dispatch problem with discrete and continuous control variables. Appl. Soft Comput., 22: 126-140.

Granville, S., 1994. Optimal reactive dispatch through interior point methods. IEEE T. Power Syst., 9(1): 136-146.

Habiabollahzadeh, H., G.X. Luo and A. Semlyen, 1989. Hydrothermal optimal power flow based on a combined linear and nonlinear programming methodology. IEEE T. Power Syst., 4(2): 530-537.

Iba, K., 1994. Reactive power optimization by genetic algorithm. IEEE T. Power Syst., 9(2): 685-692.

Jeyadevi, S., S. Baskar, C.K. Babulal and M. Willjuice Iruthayarajan, 2011. Solving multi objective optimal reactive power dispatch using modified NSGA-II. Int. J. Elec. Power, 33(2): 219-228.

Kennedy, J. and R. Eberhart, 1995. Particle swarm optimization. Proceeding of the IEEE International Conference on Neural Networks. Perth, Australia, Piscataway NJ, 4: 1942-1948.

Khazali, A.H. and M. Kalantar, 2011. Optimal reactive power dispatch based on harmony search algorithm. Int. J. Elec. Power, 33(3): 684-692.

Kirschen, D.S. and H.P. Van Meeteren, 1988. MW/voltage control in a linear programming based optimal power flow. IEEE T. Power Syst., 3(2): 481-489.

Lee, K.Y., Y.M. Park and J.L. Ortiz, 1985. A united approach to optimal real and reactive power dispatch. IEEE T. Power Ap. Syst., 104(5): 1147-1153.

Liang, C.H., C.Y. Chung, K.P. Wong and X.Z. Duan, 2006. Comparison and improvement of evolutionary programming techniques for power system optimal reactive power flow. IEE P-Gener. Transm. D., 153(2): 228-236.

Liang, C.H., C.Y. Chung, K.P. Wong, X.Z. Duzn and C.T. Tse, 2007. Study of differential evolution for optimal reactive power flow. IET Gener. Transm. Dis., 1(2): 253-260.

Liu, W.H.E., A.D. Papalexopoulos and W.F. Tinney, 1992. Discrete shunt controls in a Newton optimal power flow. IEEE T. Power Syst., 7(4): 1509-1518.

Mahadevan, K. and P.S. Kannan, 2010. Comprehensive learning particle swarm optimization for reactive power dispatch. Appl. Soft Comput., 10(2): 641-652.

Mehdinejad, M., B. Mohammadi-Ivatloo, R. Dadashzadeh-Bonab and K. Zare, 2016. Solution of optimal reactive power dispatch of power systems using hybrid particle swarm optimization and imperialist competitive algorithms. Int. J. Elec. Power, 83: 104-116.

Momoh, J.A. and J.Z. Zhu, 1999. Improved interior point method for OPF problems. IEEE T. Power Syst., 14(3): 1114-1120.

Nanda, J., D.P. Kothari and S.C. Srivastava, 1989. New optimal power-dispatch algorithm using Fletcher's quadratic programming method. IEE Proc-C, 136(3): 153-161.

Niknam, T., H.D. Mojarrad and H.Z. Meymand, 2011. A novel hybrid particle swarm optimization for economic dispatch with valve-point loading effects. Energ. Convers. Manage., 52(4): 1800-1809.

Pandya, S. and R. Roy, 2015. Particle swarm optimization based optimal reactive power dispatch. Proceeding of the IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), pp: 1-5.

Quintana, V.H. and M. Santos-Nieto, 1989. Reactive-power dispatch by successive quadratic programming. IEEE T Energ. Convers., 4(3): 425-435.

Rajan, A. and T. Malakar, 2015. Optimal reactive power dispatch using hybrid Nelder-Mead simplex based firefly algorithm. Int. J. Elec. Power, 66: 9-24.

Ramirez, J.M., J.M. Gonzalez and T.O. Ruben, 2011. An investigation about the impact of the optimal reactive power dispatch solved by DE. Int. J. Elec. Power, 33(2): 236-244.

Subbaraj, P. and P.N. Rajnarayan, 2009. Optimal reactive power dispatch using self-adaptive real coded Genetic algorithm. Electr. Power Syst. Res., 79(2): 374-381.

Tehzeeb-Ul-Hassan, H., R. Zafar, S.A. Mohsin and O. Lateef, 2012. Reduction in power transmission loss using fully informed particle swarm optimization. Int. J. Elec. Power, 43(1): 364-368.

Varadarajan, M. and K.S. Swarup, 2008. Differential evolution approach for optimal reactive power dispatch. Appl. Soft Comput., 8(4): 1549-1561.

Vlachogiannis, J.G. and K.Y. Lee, 2006. A comparative study on particle swarm optimization for optimal steady-state performance of power systems. IEEE T. Power Syst., 21(4): 1718-1728.

Wu, Q.H. and J.T. Ma, 1995. Power system optimal reactive power dispatch using evolutionary programming. IEEE T. Power Syst., 10(3): 1243-1249.

Wu, Q.H., Y.J. Cao and J.Y. Wen, 1998. Optimal reactive power dispatch using an adaptive genetic algorithm. Int. J. Elec. Power, 20(8): 563-569.

Yan, W., F. Liu, C.Y. Chung and K.P. Wong, 2006. A hybrid genetic algorithm-interior point method for optimal reactive power flow. IEEE Trans. Power Syst., 21(3): 1163-1209.

Yan, X. and V.H. Quintana, 1999. Improving an interior-point-based OPF by dynamic adjustments of step sizes and tolerances. IEEE T. Power Syst., 14(2): 709-717.

Yang, C.F., G.G. Lai, C.H. Lee, C.T. Su and G.W. Chang, 2012. Optimal setting of reactive compensation devices with an improved voltage stability index for voltage stability enhancement. Int. J. Elec. Power, 37: 50-57.

Yoshida, H., K. Kawata, Y. Fukuyama, S. Takayama and Y. Nakanishi, 2000. A particle swarm optimization for reactive power and voltage control considering voltage security assessment. IEEE T. Power Syst., 15(4): 1232-1239.