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Improvement of Reactive Power Dispatch by Using Hybrid Intelligent Optimization Technique Based on Chaotic and PSO Algorithm

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Abstract

Optimal Reactive Power Dispatch (**ORPD**) problem is a complex, non−linear, non−convex optimisation problem and contains equality and inequality constraints. The ORPD is famous and essential problems in power system analysis and control. This is not all, but added to several other objectives such as nonlinearity and minimisation problem of power system optimisation. This study concentrates on this part of Optimal Load Flow calculation. Particle Swarm Optimization (**PSO**) is better type of intelligent technique of optimization. This study employed an improved hybrid algorithm based on Chaotic **PSO** (**CPSO**). The merging of chaotic sequences in **PSO** algorithm can be an efficient method to slip very easily from local minima compared to simple **PSO** algorithm. The CPSO algorithm is used for solve economic dispatch problem. The simulation results for the IEEE node **14** and **30** power systems indicate that **CPSO** algorithm has high ability and effective in minimizing of transmission line loss and voltage profile enhancing of the system compared to simple **PSO**.

Keywords: Optimal Reactive Power Dispatch (ORPD), Optimal Load Flow, PSO, chaotic PSO (CPSO)

INTRODUCTION

Last studies correspond to about 13% of the generated power in the present power systems are wasted in distribution systems. Because several electrical loads which include reactive power, by raising the flow of electrical loads specially electrical loads that including reactive power, power loss also raising [1]. Many researchers in different studies concentrated on the optimal operation of the power system, this is because of the requesting for the electrical power has been raising vastly. The aim of Optimal Reactive Power Dispatch (ORPD) problems include to minimise the loss of transmission line in the power system and to keep voltage at all buses with an acceptable levels while deals with a number of equality and inequality constrains [2].

Carpentier J. was introduced calculation of Optimal Power Flow (OPF) in (1962s) [3]. Then several researchers have been focused on this problem with different methodologies. The calculation of economic dispatch optimisation problem is really part from calculation of optimal power flow. This problem is also consist of many objective functions and non−linear problems [4-6].

Khazali and Kalantar in (2011) have presented Harmony Search (HS) approach in solving (ORPD) optimisation problem. In this approach objective functions are handled separately and the inequality limits such as reactive power generation (Q_g) and voltages at load buses (V_l) are treated by penalty factors. The results presented on IEEE node 30 and node 57 systems and these results are compared with the results calculated by Genetic (GA) and PSO algorithms [7, 8].

Other groups of researchers were dealing with a multi objective function by a new enhancement Teaching Learning Based Optimization (TLBO) technique that is utilized for solve economic dispatch optimization problem by reducing the objective functions [9-12]. Varadarajan and Swarup in (2008) have showed the ORPD as a non-linear optimization problem with penalty functions for constraint treating. TLBO approach is implemented on IEEE 14 –node, 30 −node and 118 −node systems [13]. A fuzzy adaptive PSO using for voltage security and reactive power have been represented in reference [14], Zhao in (2005) has been solved ORPD problem using multi-agent-based PSO [15]. And at last a stochastic reactive power dispatch problem was purposed by GA in the study [16].

In this study, to enhance searching ability of the PSO technique and to avoid a drop it into the early convergence to local minima and to decrease the calculation time, Chaotic PSO (CPSO) is used in order to overcome this drawback. This hybrid CPSO algorithm helps to slip from the local optima due to the special behavior, high ability, and require less time compared with simple PSO. The simple PSO and improved CPSO are used individually for ORPD problem to assess the decreasing active power losses and enhancing voltage of the system. Moreover, simulations and results of ORPD problem have been implemented for standard IEEE 14 and 30 node power systems.

ORPD PROBLEM

ORPD is a non−linear optimization problem. For achieving the reliability and proficiently for the power system, the decreasing real power loss and voltage level should be handled and satisfying the equality and inequality constrains. The multi objective ORPD problems are utilized to optimize one objective function or some objective functions and satisfying the constraints of the problem [17-21].

Problem Formulation

$$\text{Min } P_{loss} = J(x, u) \quad (1)$$
$$\text{Subjected to: } eq(x, u) = 0$$
$$\text{and } ieq(x, u) \leq 0$$

from equation (1), (J) is represent the objective function that formulated to minimize (Min) the total active power loss (P_{loss}) of the system; (eq, ieq) the equality and inequality constrains, and also they are equations of load flow. Also, the control variables vector (u) is contains:

1. Output real power for any generator (P_G) except the output real power in slack node (P_{G-1}).
2. Voltage at generation node (V_G).
3. Transformer tap (Tap).
4. Source of VAR compensation (capacitor bank Q_c).

and (x) is the dependent variables vector (security constrains) and contains:

1. Output power at a slack node (P_{G-1}).
2. Voltage at load nodes (V_l).
3. Generated reactive power (Q_G).
4. Transmission apparent power flow (S_L).

Constrains

Equality constrains

These constrains are equations of load flow, as shown below [6].

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

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

From equation (2) and equation (3), the number of total nodes is NB, the generated output active power at i node is P_{Gi} and the generated output reactive power at i node is Q_{Gi}, the load real power at i node is P_{Di} and the load reactive power at j node is Q_{Di}, G_{ij} is the mutual conductance and B_{ij} is the mutual susceptance among i node and j node, V_i is the absolute value of voltage value at i node and V_j is the absolute value of voltage in j node; ϕ_{ij} is the difference angle for voltage between node i and node j, respectively.

Inequality constrains

These constrains contain:

Constrains of generator: These constrains contains of generator voltage V_G, active P_G and reactive Q_G output power of all generator and limited by their minimum maximum limits.

$$V_{G-i}{}^{min} \leq V_{G-i} \leq V_{G-i}{}^{max}, \quad i = 1, \dots \dots, N_G \quad (4)$$

$$P_{G-i}{}^{min} \leq P_{G-i} \leq P_{G-i}{}^{max}, \quad i = 1, \dots \dots, N_G \quad (5)$$

$$Q_{G-i}{}^{min} \leq Q_{G-i} \leq Q_{G-i}{}^{max}, \quad i = 1, \dots \dots, N_G \quad (6)$$

Transformer constrains: this constrain contain of transformer positions T_i have lower and upper limits.

$$Tap_i{}^{min} \leq Tap_i \leq Tap_i{}^{max}, \; i = 1, \dots \dots, N_T \quad (7)$$

Source VAR constrains: switchable VAR source Q_C is bounded as given in equation (8):

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

Security constrains: these constrains contain the restrictions of voltages at load node V_l and apparent power flow S_L as shown below:

$$V_{l-i}{}^{min} \leq V_{l-i} \leq V_{l-i}{}^{max}, \; i = 1, \dots \dots, N_{PQ} \quad (9)$$

$$S_{L-i} \leq S_{L-i}{}^{max} \qquad i = 1, \dots \dots, N_L \quad (10)$$

Objective Functions

The dependent variables can be added to equation (1) by using penalty factors to constrain. Therefore, equation (1) can be represented as shown below [22]:

$$min\, J = P_{loss} + \lambda_P (p_{G1} - p_{G1}{}^{lim})^2 + \lambda_V \sum_{i=1}^{NL} (v_{Li} - v_{Li}{}^{lim})^2 + \lambda_Q \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}{}^{lim})^2 + \lambda_S \sum_{i=1}^{NL} (s_{Li} - s_{Li}{}^{lim})^2 \quad (11)$$

in equation (11), λ_P, λ_V, λ_Q, and λ_S are penalty terms; X^{lim} is the limit value of inequality constrains; and P_{loss} is given by the following equation:

$$P_{loss} = \sum_{K=1}^{Ntl} G_K (V_i{}^2 + V_j{}^2 - 2V_i V_j cos(\phi_i - \phi_j)) \quad (12)$$

from equation (12), Ntl is the total number of branches, G_K is the conductance of line K, V_i is the voltage at node i, V_j is the voltage at node j, ϕ_i is the angle of voltage at i node and ϕ_j is the angle of voltage at j node.

Concept of Average Voltage

In this study, a new index of average voltage is proposed to manage all voltage nodes (buses) and satisfy most of the electrical utility constraints. This index is given in equation (13).

$$V_{av} = \frac{\sum_{i=1}^{Nn} V_i}{N_n} \quad (13)$$

where V_{av} is the average voltage of the system; the voltage in node i is referred to as V_i, and the total number of nodes is referred to as N_n.

PSO ALGORITHM

PSO algorithm is fast, simple, robust and differs from Genetic and some heuristic approach's, which has high flexibility to control the balance among the global g_{best} as well as local p_{best} positions to explore the problem space, and population based on the above mentioned algorithm. Eberhart was first introduced this approach in (1995s) [15, 23]. It has been described the behavior of groups such as flock school fish or swarms of birds to adapt with their surrounding environment in order to search for abundant food sources and avert the risk of predators. PSO is deemed fast and needs less memory due to simplicity of this algorithm. The approach starts with random positions of swarm population in the problem space. Every swarm is considered as a solution of the problem and has a fitness value. All agents have a memory and monitor the individual best position (p_{best}) as well as the relating fitness value. The agent has another best value which is called global best position (g_{best}) which is the better value among all swarm (p_{best}). The current position for all particles are updated based on its local (p_{best}) and global (g_{best}) position. The velocity and position can be updated by utilizing equation (14) and equation (15), and then the resulting two equations can be obtained [24].

$$v_i^{k+1} = K*[W*v_i^{k} + C_1 * r_1*({p_{best(i)}}^{k} - x_i^{k}) + C_2 r_2*({g_{best(i)}}^{k} - x_i^{k})] \quad (14)$$

$$x_i^{k+1} = x_i^{k} + v_i^{k+1} \quad (15)$$

from the above equations:

v_i^{k+1} : is the velocity of agent at $(k+1)$ iteration.

w : is the inertia weight factor.

v_i^{K} : is the velocity of agent at current iteration.

C_1, C_2 : are the two positive constants within $[0 - 2.05]$.

r_1, r_2: are the uniformly distributed positive random numbers within limit [0−1].

${p_{best(i)}}^{k}$: is the local best value at (k) iteration.

${g_{best(i)}}^{k}$: is the global best value at(k)iteration.

x_i^{k+1} : is the position at $(K+1)$ iteration.

x_i^{k} : is the position at current iteration.

K: The constriction factor and it is use to guarantee the convergence of PSO, it was introduced by Shi indicate that use of this factor may be important and can be express as follow [25].

$$K = \frac{2}{\left|2-\phi-\sqrt{\phi^2-4\phi}\right|}, \quad \phi = C_1 + C_2,\ \phi \geq 4 \quad (16)$$

Now, (W) is reduced from (0.9 to 0.4) linearly at each iteration to achieve efficiently trade-off between capabilities of the global exploration and local exploitation as follows:

$$W = W_{max} - \frac{W_{max} - W_{min}}{max_{iteration}} * iter \quad (17)$$

from equation (17):

W_{max} : is the max value of weight.

W_{min} : is the min value of weight.

$iter$: is the current iteration.

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

CHAOTIC PARTICLE SWARM OPTIMIZATION (CPSO)

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. A chaos theory merged with a PSO algorithm to form a hybrid algorithm CPSO and this way helped the CPSO algorithm to slip from the local optima due to the special behaviour and high ability of the chaos [26]. In this study, the logistic sequence equation adopted for establishing the hybrid CPSO algorithm is described by the following equation [27].

$$\beta^{k+1} = \mu\beta^{k}((1-\beta^{k})), \quad 0 \leq \beta^{1} \leq 1 \quad (18)$$

From equation (18), the control parameter μ is set within a range [0.0−4.0], k is the number of the iterations. The magnitude of μ decides whether β stabilizes at a constant area, oscillates within restricted limits, or behaves chaotically in an unpredictable form. And equation (18) is deterministic, it shows chaotic dynamics when μ = 4.0 and $\beta^{1} \in \{0, 0.25, 0.5, 0.75, 1\}$. It shows the sensitive depend on its initial conditions, which is the basic features of chaos. The new inertia weight factor (W_{new}) is calculated by multiplying the (W) in equation (17) and logistic sequence in equation (18) as follows.

$$W_{new} = W * \beta^{k+1} \quad (19)$$

To enhance the behavior of the simple PSO, this study presents a new velocity change by incorporating a logistic sequence equation with inertia weight factor. Finally, by substituting equation (19) with equation (14), the following velocity updated equation for the proposed CPSO is obtained:

$$v_i^{k+1} = W_{new} * v_i^{k} + C_1*r_1*({p_{best(i)}}^{k} - x_i^{k}) + C_2*r_2*({g_{best(i)}}^{k} - x_i^{k}) \quad (20)$$

In the CPSO W_{new} is a decrease and oscillates simultaneously for total iteration from (0.9 to 0.4).

REPRESENTATION OF CPSO FOR SOLVING ORPD

The CPSO 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 equations (20) and (15) 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.

CASE STUDY AND RESULTS

To improve the efficiency, accuracy and high ability of CPSO algorithm and also to search for the optimization solution for decreasing losses and improving system voltage. Standard IEEE node−14 and node−30 systems are utilized to examine and test the proposed approach. PSO and CPSO algorithms have been represented in MATLAB programing language.

IEEE 14-Node System

Bus, branch and generator data for standard IEEE 14 –node power system are given in the reference [28]. This standard system contains 20 lines, 5 generators, 3 transformers and 1 shunt capacitor. Thus, standard IEEE node−14 power system has 9 dimensions search space and their settings are given in Table 1 and the bounds for reactive power generation in MVAR are shown in the Table 2 [20]. Figures 1 and 2 shows the convergence characteristics, and Figure 3 shows voltage profile for this standard system before and after PSO and CPSO algorithms.

Table 1: Control Variables Limits.

IEEE bus−14	Independent Variables	Min	Max
14 Bus	Generator Voltage (VG)	0.95	1.1
	Transformer Tap (OLTC)	0.9	1.1
	VAR Source (QC)	0	0.20

Table 2: Constrains Of Reactive Power Generation.

IEEE bus−14	Generator Variables	Q_{Min}	Q_{Max}
14 Bus	1	0	10
	2	-40	50
	3	0	40
	6	-6	24
	8	-6	24

The simulation results for IEEE 14-node system and comparison with EP and SARGA algorithms [29] which are given in Table 3.

Table 3: Simulation Results Of IEEE Node−14Systems.

Control Variables	Base Case	CPSO	PSO	EP [29]	SARGA [29]
V_{G-1}	1.060	1.100	1.100	-	-
V_{G-2}	1.045	1.087	1.086	1.029	1.060
V_{G-3}	1.010	1.058	1.056	1.016	1.036
V_{G-6}	1.070	1.095	1.067	1.097	1.099
V_{G-8}	1.090	1.100	1.060	1.053	1.078
Tap_{4-7}	0.978	0.975	1.019	1.04	0.95
Tap_{4-9}	0.969	0.975	0.988	0.94	0.95
Tap_{5-6}	0.932	1.018	1.008	1.03	0.96
Q_{C-9}	0.19	0.186	0.185	0.18	0.06
Total P_L (Mw)	13.550	12.243	12.315	13.34620	13.21643

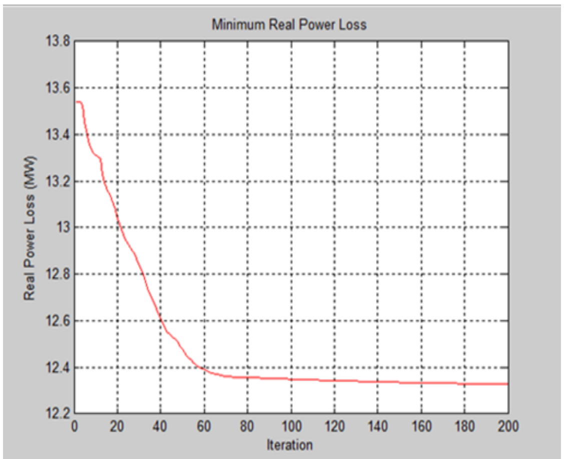

Figure 1: Convergence for IEEE 14 Node Power System with PSO Algorithm.

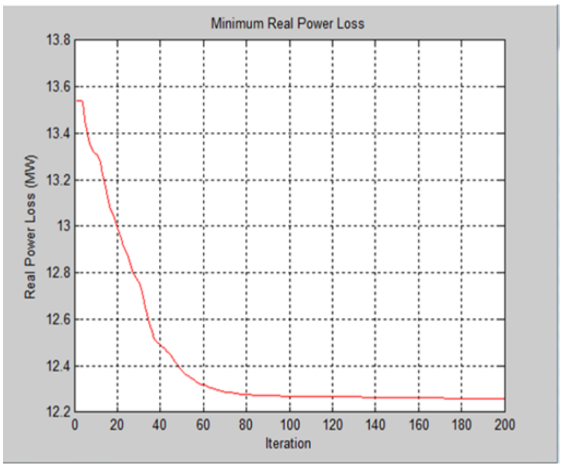

Figure 2: Convergence for IEEE 14 Node Power System with CPSO Algorithm.

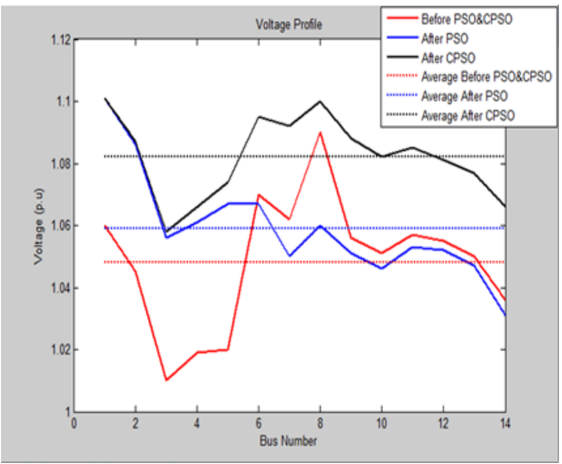

Figure 3: Voltage Profile for IEEE 14 Node Power System.

IEEE 30-Node System

Bus, branch and generator data for IEEE 30-node systems are given in reference [28]. They are contains 41 branches, 6 generators node, 4 transformers ratio and 2 VAR sources (capacitor banks) connected in IEEE 30-node system. Therefore, this system has 12 dimensions search space and their settings are tabulated in Table 4 and the bounds of generator reactive power in MVAR are shown in the Table 5 [28].

Table 4: Control Variables Limits.

IEEE bus−30	Variables	Min	Max
30 Bus	Generator Voltage VG	0.95	1.1
	Transformer Position (OLTC)	0.9	1.1
	VAR Source QC	0	0.20

Table 5: Constrains Of Reactive Power Generation.

IEEE bus−30	Generator Variable	Q_{Min}	Q_{Max}
30 Bus	1	0	10
	2	-40	50
	5	-40	40
	8	-10	40
	11	-6	24
	13	-6	24

The simulation results for IEEE 30-node system and comparison with EP, SARGA [29], DE, DE−ABC and ABC [20] algorithms which are given in Table 6.

Figures 4 and 5 shows the convergence of standard IEEE node 30 power system. Figure 6 show the voltage profile of this standard power system before and after PSO and CPSO algorithms.

It is clear that from Figure 6, average voltage at initial is about **1.029** and at PSO is about **1.035** and at CPSO is about **1.050**.

Table 6: Simulation Results of IEEE- 30 Node System.

Control Variables	Base case	CPSO	PSO	EP [29]	SARGA [29]
V_{G-1}	1.060	1.100	1.100	-	-
V_{G-2}	1.045	1.086	1.072	1.097	1.094
V_{G-5}	1.010	1.052	1.038	1.049	1.053
V_{G-8}	1.010	1.059	1.048	1.033	1.059
V_{G-11}	1.082	1.083	1.058	1.092	1.099
V_{G-13}	1.071	1.100	1.080	1.091	1.099
Tap_{6-9}	0.978	1.008	0.987	1.01	0.99
Tap_{6-10}	0.969	0.993	1.015	1.03	1.03
Tap_{4-12}	0.932	1.024	1.009	1.07	0.98
Tap_{28-27}	0.968	0.987	1.012	0.99	0.96
Q_{C3}	0	0	0	0.19	0.19
Q_{C10}	0.19	0.077	0.077	0.04	0.04
Q_{C24}	0.043	0.123	0.128	-	-
Total P_L (Mw)	17.55	16.01	16.25	16.38	16.09
	DE[20]		DE−ABC [20]		ABC[20]
	16.3176		16.2163		16.59

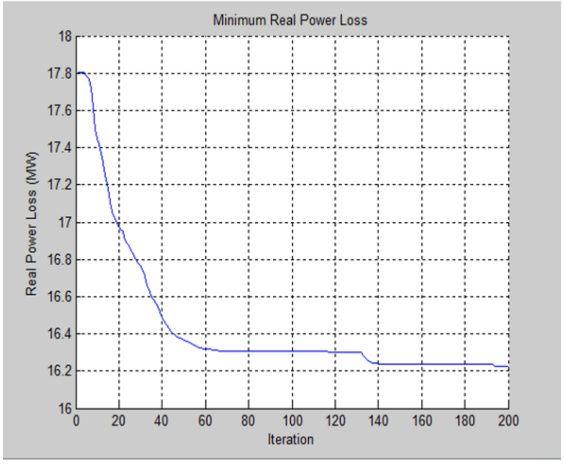

Figure 4: Convergence of IEEE 30-Node System with PSO Algorithm.

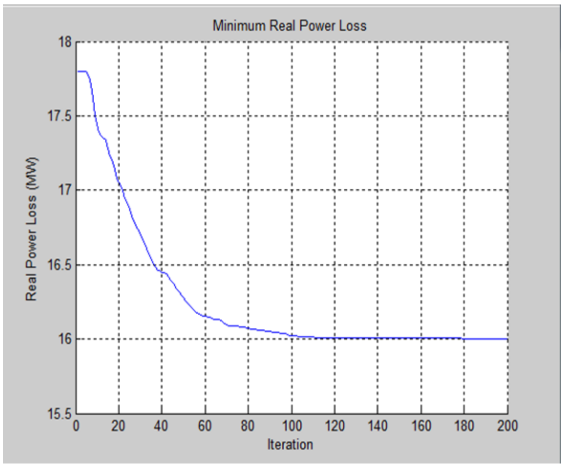

Figure 5: Convergence of IEEE 30-Node System with CPSO Algorithm.

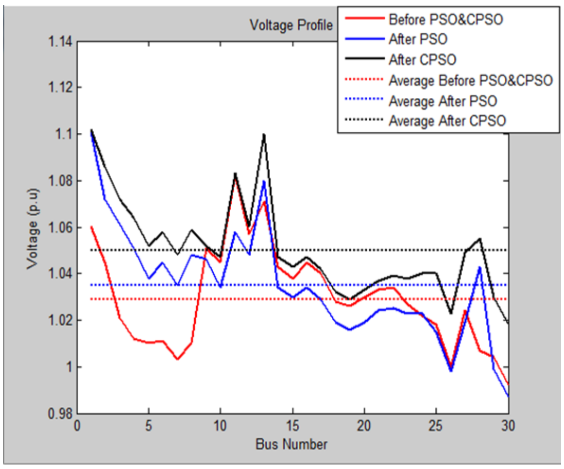

Figure 6: Voltage Profile of IEEE 30-Node System.

CONCLUSIONS

In this study, PSO and chaotic PSO algorithms are employed for ORPD problem. The goal of using objective function is to decreasing branch loss as well as voltage profile enhancement of power system. The efficiency and higher speed of convergence of CPSO algorithm and also decrease in time calculation has been proved by examining on IEEE node 14 and 30 standard power systems. The simulation results are compared with multi algorithms that presented in the literature. It is prove, the results of chaotic particle swarm optimization (CPSO) in this study are best results and high accuracy than the results calculated in simple PSO approach and other results reported in the literature.

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