Journal of Engineering and Applied Sciences 14 (7): 2112-2123, 2019
ISSN: 1816-949X

Optimal Capacitor Sizing for Reactive Power Optimization by Using a New Hybrid Algorithm Based on Merging of Chaotic Strategy with PSO Algorithm

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Abstract: Reactive power optimization is recorded as a complex, non linear and very important problem for keeping the power system running under normal conditions. In this study, original Particle Swarm Optimization (PSO) and Chaotic (CPSO) algorithms are utilized as an optimization tools for the solution of this problem. Two types of loads are presented in this problem: the constant loads (light) and variable loads (heavy) are presented to evaluate and test the efficiency and consistency of the CPSO algorithm for solving this problem when the load is changing. In this study in order to prevent plunge at the premature convergence to the local optima, also to improving the quality and search ability of the original PSO algorithm, chaotic strategy is incorporating with PSO algorithm to form a hybrid algorithm called CPSO algorithm. This incorporating is very helping to slip more easily from the local optima, to get accurate solution and also to reach optimal solution in less number of iterations compared to original PSO algorithm and other algorithms in the literature due to the special behavior and ergodic of the chaos strategy than random search in original PSO algorithm. In this problem, the decreasing of real Power Loss (P_L) is an objective function while dealing with some of inequality and equality constrains. The calculations of reactive power optimization are a part of Optimal Power Flow (OPE) calculations. The original PSO and CPSO algorithms are tested on IEEE Standard-14 and-30 bus systems. The simulation implications indicate that, CPSO algorithm has best convergence characteristic and obtained solutions close to the optimal results for reducing power loss and dealing with inequality and equality constrains at the same time comparison with original PSO and other techniques in the literature for constant loads and comparison with original PSO for the case of variable loads.

Key words: Reactive power optimization, Optimal Power Flow (OPF), PSO, Chaotic PSO (CPSO)

INTRODUCTION

Reactive power optimization is considered as a complex and multi constraint optimization problem. It is a very essential and important problem and it is utilizing to find economic, reliable and safe operating for the power systems by a proper adjustments of reactive power parameters like generator Voltages (V_G), transformers ratio (Tap) and the size of injected reactive power VAR source [shunt Capacitors (Q_C) or shunt reactors (X_L)] while dealing with some of equality and inequality constrains and also can control the flow of reactive power (VAR) in the systems (Khazali and Kalantar, 2011; Pires *et al*., 2012). The objective of this problem is to decrease power losses and enhance voltage profiles of the system and this objective can be done by control (V_G, Tap and the amount of shunt Q_C or X_L) (Lai *et al*., 2005). The electric power loads are changed from time to time and not constant and this change may cause reduce or raise voltages at nodes as well as the electrical losses due to increasing the flow of reactive power (Khazali and Kalantar, 2011). At no load conditions, load want the reactive power (VAR) for magnetizing purposes but on load conditions, it needs the reactive power (VAR) by the relying on the type of the load which is mainly determined by the configuration of the magnetic circuit. Reactive power devices adjustment are change continuously with the voltage level and the load because the control of voltage in the power system is greatly depended and associated with the control on the amount of the reactive power (Mahadevan and Kannan, 2010). The advantages of this problem behind the control of reactive power are decrease in the power losses, enhancement of both voltage profile and power factor (Aldrich *et al*., 1980).

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Undeniably, over the last decades, this problem plays a vital role in the power system and has recorded an ever growing interest of the researech because of remarkable effect on the economic, safe and security operation problem.

This problem is really a part of Optimal Load Flow or (OPF) calculation were first introduced the formulation of OPF calculations (Dommel and Tinney, 1968). Carpentier was developed OPF calculations in year 1979. Then, many researchers have been working on solving OPF problem by utilizing multi methods, like recursive quadratic, linear and nonlinear programing and interior point method (Habibollahzadeh *et al*., 1989; Aoki *et al*., 1987; Yan and Quintana, 1999; Momoh and Zhu, 1999).

Several traditional optimization methods has been presented for solving many complex and non continuous optimization problems, like Differential Evolution (DE) (EL Ela *et al*., 2011; Bhattacharya and Chattopadhyay, 2011), Gradient Search (GS) (David *et al*., 1986), Interior Point methods (IP) (Granville, 1994) and Linear Programming (LP) (Aoki *et al*., 1988; Deeb and Shahidehpour, 1988). Zhu *et al*. have presented a new method to solve optimal reactive power (volt-ampere-reactive) problem utilizing Modified Interior Point (MIP) technique to reduce power losses and to deal with one new (VAR) utilization (Zhu and Xiong, 2003). These traditional methods have many disadvantages, like excessive big time, big numerical iterations in resulting, slip to the local optima, difficulty in solving problem that contain very large number of variables, not able for dealing with non-linear and insecure convergence characteristic. For these disadvantages, research has developed and enhanced heuristic based algorithms for the solution of complex problem and able to prevents these disadvantages (El-Ela *et al*., 2010).

Recently, several heuristic methods has been presented for solving reactive power optimization like, Genetic Algorithm (GA), improved GA, real parameter GA, adaptive (Durairaj *et al*., 2006, 2008; Devaraj, 2007; Cao and Wu, 1997), Particle Swarm Optimization (PSO) (Yoshida *et al*., 2000), hybrid PSO (Esmin *et al*., 2005), Bacterial Foraging Optimization (BFO) (Tripathy and Mishra, 2007), Evolutionary Programming (EP) (Wu and Ma, 1995), Differential Evolution (DE) (EL Ela *et al*., 2011; Bhattacharya and Chattopadhyay, 2011; David *et al*., 1986; Granville, 1994; Aoki *et al*., 1988; Deeb and Shahidehpour, 1988; Zhu and Xiong, 2003; El-Ela *et al*., 2010; Durairaj *et al*., 2006; Devaraj, 2007; Devaraj *et al*., 2008; Cao and Wu, 1997; Yoshida *et al*., 2000; Esmin *et al*., 2005; Tripathy and Mishra, 2007; Wu and Ma, 1995; Liang *et al*., 2007; Varadarajan and Swarup, 2008), Seeker Optimization Algorithm (SOA) (Dai *et al*., 2009) and Gravitational Search Algorithm (GSA) (Duman *et al*., 2012), etc. These techniques have been presented to prevent the disadvantages of traditional optimization methods. Cao *et al*. presented a solution to the problem with a novel PSO algorithm based on Multi Agent PSO (MAPSO) and this algorithm is presented on IEEE node-30 system (Zhao *et al*., 2005). Presented Hybrid Stochastic Search (HSS) for the solution of the RPD problem and this technique is examined on IEEE-118 node system (Das and Patvardhan, 2002). Nakanishi *et al*. have utilized for reactive power as well as voltage control and compared their implications with the Reactive Tabu System (RTS) and presented this technique on a practical power system (Yoshida *et al*., 2000). Zhang *et al*. have presented adaptive for solving reactive power (VAR) optimization problem (Zhang and Sanderson, 2009). Kumari and Sydulu (2006) have utilized improved PSO or the solving of optimal reactive power (VAR) problem. Lee *et al*. have presented three new algorithms presented on two test systems for solving reactive power as well as voltage control (Vlachogiannis and Lee, 2006). Li *et al*. (2009) have presented parallel PSO for solving dynamic ORPD problem. As said by this theorem “No Free Lunch (NFL)”, there is no optimisation approach that can solve whole the optimization problem. Therefore, searching of a new approach is still necessary for solving the said problem.

In this study, so as to enhance the convergence characteristic, quality, performance and to prevent the problem from stick in the local optima in order to become premature convergence in the original PSO technique, a chaotic strategy merged with PSO technique to form a hybrid algorithm called Chaotic PSO (CPSO) technique. This algorithm is helped more easily to slip from the local optima due to the special behavior, dynamic properties and ergodic of chaos strategy than random search in original PSO approach. Original PSO and CPSO algorithms are utilized for the solution of reactive power optimization so as to decreasing the real power losses and voltage profile improvement of the system. These algorithms are tested on IEEE node-14 and-30 system for constant and heavy (variables) loads where the load was changed from constant load to heavy load in this study, so as to examining and evaluating the ability and reliability of these algorithms to solve this problem at any change in loads. For heavy load (constant real and reactive) power load demand at base case is multiplied by (μ) factor where represents the ratio magnitude for the load variation. From the simulations implications indicate that CPSO technique has high ability, best convergence characteristic, robustness and effective for solving complex and non linear problem compared to original PSO and some algorithms in the literature for constant loads and compared to original PSO approach only for variable loads.

MATERIALS AND METHODS

Problem formulation

Objective function: The great objective for this study is to decrease the power losses for the system through a proper adjustment of reactive power requirments while dealing with numbers of variables (i.e., equality and inequality) constrains at the sometime which can be expressed as shown (Rajan and Malakar, 2015) from Eq. 1:

$$\text{Min } P_{loss} = \sum_{K=1}^{Ntl} G_K\left(V_i^2+V_j^2-2V_iV_j\cos(\Phi_i-\Phi_j)\right) \quad (1)$$

Where:

- N_{tl} = The No. of branches
- P_{loss} = The active Power losses
- G_k = The conductance of line
- V_i = The Voltage value at node
- V_j = The Voltage value at node
- Φ_i, Φ_j = The difference angles voltage at node i and j

Subjected to equality constrains (load flow equations) from Eq. 2 and 3:

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

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

- NB = Depicts the number of nodes in the system
- P_{Gi}, Q_{Gi} = The real (MW) and reactive power (MVAR) output from the generators at node
- P_{Di}, Q_{Di} = The real (MW) and reactive power (MVAR) load demand at node
- G_{ij}, B_{ij} = The mutual and susceptance conductance among node and node
- Φ_{ij} = The voltage angle magnitude in node i and j

and a number of inequality constrains and that involves two types of these constrains as illustrated below: A-independent (control) variables such as (Rajan and Malakar, 2015) from Eq. 4-6:

$$V_{G\text{-}i}^{min} \le V_{G-i} \le V_{G\text{-}i}^{max}, i\in N_G \quad (4)$$

$$Tap_K^{min} \le Tap_K \le Tap_K^{max}, K\in N_T \quad (5)$$

$$Q_{C\text{-}i}^{min} \le Q_{C\text{-}i} \le Q_{C\text{-}i}^{max}, i\in N_C \quad (6)$$

Where:

- N_G = The No. of Generator nodes
- $V_{G\text{-}i}^{min}$, $V_{G\text{-}i}^{max}$ = Are the Minimum (Min) limit and Maximum (Max) limit of Generator Voltage value at I-node node
- N_T = Is the total No. of Transformers
- Tap_i^{min}, Tap_i^{max} = Are the Minimum (Min) limit and Maximum (Max) limit of Transformer ratio at branch
- N_C = The total No. of Capacitor banks
- $Q_{C\text{-}i}^{min}$, $Q_{C\text{-}i}^{max}$ = The Minimum (Min) limit and Maximum (Max) limit of injected VAR source from shunt capacitor at node I

B-dependent (state) variables such as (Rajan and Malakar, 2015) from Eq. 7 and 8:

$$Q_{G\text{-}i}^{min} \le Q_{G\text{-}i} \le Q_{G\text{-}i}^{max}, i\in N_G \quad (7)$$

$$V_{l\text{-}i}^{min} \le V_{l-i} \le V_{l\text{-}i}^{max}, i\in N_{PQ} \quad (8)$$

Where:

- N_G = The No. of Generator nodes
- $Q_{C\text{-}i}^{min}$, $Q_{C\text{-}i}^{max}$ = The Minimum (Min) limit and Maximum (Max) limit of reactive power output of generator at node
- N_{PQ} = The No. of load nodes
- $V_{l\text{-}i}^{min}$, $V_{l\text{-}i}^{max}$ = The Minimum (Min) limit and Maximum (Max) limit of voltage value at node

The generalized fitness function: In this study, V_G, Tap and Q_C are the independent (control) variables, therefore, V_G, Tap and Q are self constrained. The state (dependent) variables V_L and Q_G are constrained by utilizing penalty factors by merging them to the objective function (Eq. 1), so, Eq. 1 can be written as shown below in Eq. 9 (Rajan and Malakar, 2015):

$$\text{Min } F = P_{loss}+\lambda_V\sum_{i=1}^{NL}\left(\nu_{Li}-\nu_{Li}^{lim}\right)^2+\lambda_Q\sum_{i=1}^{NG}\left(Q_{Gi}-Q_{Gi}^{lim}\right)^2 \quad (9)$$

Where:

- P_{loss} = Described in Eq. 1
- λ_v, λ_Q = The penalty terms
- NL = The No. of Loads nodes that outside the limits
- NG = The No. of reactive power output of Generator nodes that outside the bounds
- ν_{Li}^{lim}, Q_{Gi}^{lim} = The bounds of dependent (state) variables, given as:

$$\nu_{Li}^{lim} = \begin{cases} \nu_{Li}^{min} & \text{if } \nu_{Li} < \nu_{Li}^{min} \\ 0 \text{ if } \nu_{Li}^{min} \le \nu_{Li} \le \nu_{Li}^{min} & \\ \nu_{Gi}^{max} & \text{if } \nu_{Li} > \nu_{Li}^{max} \end{cases} \quad (10)$$

$$Q_{Gi}^{lim} = \begin{cases} Q_{Gi}^{min} & \text{if } \nu_{Li} < Q_{Gi}^{min} \\ 0 \text{ if } Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} & \\ Q_{Gi}^{max} & \text{if } \nu_{Li} > Q_{Gi}^{max} \end{cases} \quad (11)$$

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. Equation 12 of this concept can be written as shown below:

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

Where:

$V_{\alpha v}$ = The average Voltage of all system
V_i = The Voltage in node i
N_n = The total No. of nodes

Optimization process

Original PSO algorithm: PSO technique is a kind of a stochastic optimization, the idea of PSO algorithm come from the behavior of animals that do not have leader in the population or group, so, it has random behavior when will search for food like bird flocking and fish schooling. It is fast, simple, robust and high quality within lesser calculation time in solving non-linear and complex optimization problem. It was first introduced by Kennedy and Eberhart (1995). It is very similar to other stochastic techniques like genetic algorithm but differs from genetic algorithm that does not contain some of genetic operators like mutation and crossover and also PSO algorithm has memory that is necessary to the algorithm. Every solution is defined as an individual. An individual presented as possible solution. The collection of individuals is called as a swarm. The number of the search space dimensions is equal to the number of variables in the issue, individual will flying through the dimensions of the search space of the problem to search for the best position in that space. Each individual has optimal solution (position) found by the individual itself and stored in special memory called local best position (p_{best}) and the best solution (position) found between the whole individuals in the populations (p_{best}) also stored in a memory called global best position (g_{best}), at every iteration these positions will updated. At every iteration (step), the velocity and position from position and g_{beast} position of the individuals will be modified by utilizing Eq. 13 and 14 (Vlachogiannis and Lee, 2006):

$$\nu_i^{k+1} = K * \left[\begin{matrix} W_{PSO} * \nu_i^k + C_1 * R_1 * \left(p_{best(i)}^{\ k} - x_i^k\right) + \\ C_2 * R_2 * \left(g_{best(i)}^{\ k} - x_i^k\right) \end{matrix} \right] \quad (13)$$

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

Where:

ν_i^{k+1} = The velocity of agent in iteration (K+1)
W_{PSO} = The inertia coefficient
ν_i^k = The velocity of agent in current iteration
C_1, C_2 = The Cognitive and asocial positive constants that utilize to pull every individual on the way to p_{best} position and g_{best} position within range [0-2.05]
R_1, R_2 = The two Random numbers within limit [0-1]
$p_{best\ (i)}^{\ k}$ = The personal best solution in iteration k
$g_{best\ (I)}^{\ k}$ = The global best solution in iteration k
x_i^{k+1} = The position in iteration
x_i^k = The position in iteration k
K = The constriction factor

It is utilize to guarantee the convergence of original to a stable point, without want for velocity fixing and it was introduced by Shi indicate that using of this factor may be necessary and can be expressed as follow (Reddy and Reddy, 2008):

$$K = \frac{2}{|2 - \Phi - \sqrt{\Phi^2 - 4\Phi}\,|}, \quad \Phi = C_1 + C_2, \ \Phi \ge 4 \quad (15)$$

In this study, (W_{PSO}) is reduced from (0.9-0.4) linearly at iterations to search in a big area at the start of the simulation and to attain balance between global exploration (g_{best}) and local exploitation (p_{best}) as follows:

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

Where:

W_{max} = The max (upper) value of weight
W_{min} = The min (lower) value of weight
iter = The current iteration
$max_{iteration}$ = The max (upper) iterations

CPSO algorithm: In spite of the advantages of original PSO algorithm but often it has some disadvantages similar to the other techniques and the main disadvantages in original PSO algorithm is highly depends on its parameters, not sure to be global convergence and plunge to the local optima near optimal solution when the problem is very complex and contains very large numbers of variables. In order to prevents these disadvantages and to enhance the quality and convergence characteristic, a

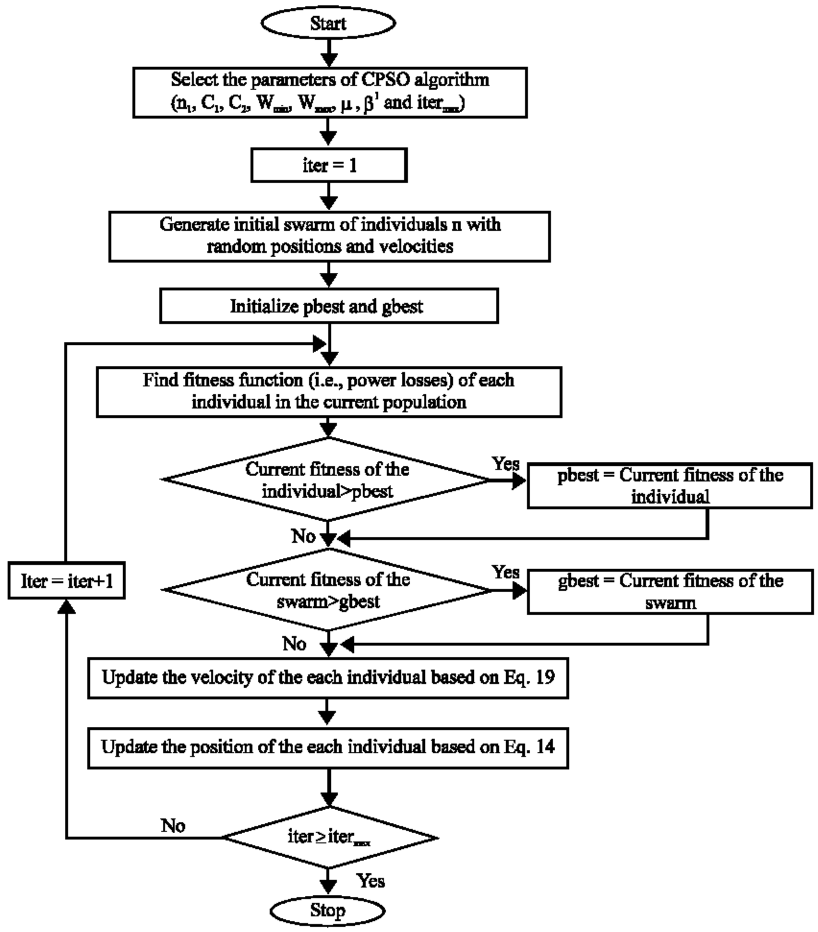

Fig. 1: CPSO algorithm for solving reactive power optimization problem

chaos strategy merged with a PSO algorithm to form a hybrid algorithm called CPSO and this way helping the CPSO algorithm to slip from the local optima and to get rapid convergence to the global solution due to the special behaviour and high ability of the chaos strategy than random search in original PSO algorithm (Hussain *et al*., 2013). In this study, the logistic sequence Eq. 17, adopted for establishing the hybrid CPSO algorithm is described by the following equation (Yang *et al*., 2007):

$$\beta^{k+1} = \mu\beta^k\left(\left(1\text{-}\beta^k\right)\right),\ 0 \leq \beta^1 \leq 1 \tag{17}$$

From Eq. 17, the control parameter 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 Eq. 17 is deterministic, it shows chaotic dynamics when μ = 4.0 and $\beta^1 \epsilon \{0, 0.25, 0.5, 0.75, 1\}$. It shows the sensitive depend on its initial conditions which is the basic features of chaos.

The new inertia weight factor (W_{CPSO}) is calculated by multiplying the (W_{PSO}) in Eq. 16 and logistic sequence in Eq. 17 and 18 as illustrates:

$$W_{CPSO} = W_{PSO} * \beta^{k+1} \tag{18}$$

To enhance the behavior and the searching ability of the original, this study presents a new velocity change by merging a logistic sequence equation (β) with inertia weight factor (W_{PSO}). Finally, by merging Eq. 16 and 17 the following velocity updated Eq. 19 for the proposed CPSO is obtained (Fig. 1):

$$\begin{aligned} v_i^{k+1} = W_{CPSO} * v_i^k + C_1 * r_1 * \left(p_{best(i)}^k \text{-} x_i^k\right) + \\ C_2 * r_2 * \left(g_{best(i)}^k \text{-} x_i^k\right) \end{aligned} \tag{19}$$

In the CPSO algorithm, is decrease and oscillates simultaneously from (0.9-0.4) for total iteration but in original PSO is reducing linearly. Figure 1 shows the flowchart for the CPSO algorithm.

Table 1: Control variables limits for IEEE 14-node system

IEEE bus/independent variables	Min	Max
14 bus		
Generator Voltage (V_G)	0.95	1.10
Transformer Tap (Tap)	0.90	1.10
VAR source compensation (Q_C)	0.00	0.20

Table 2: Constrains of reactive power generation for IEEE 14-node system

IEEE bus/generator nodes	Q_{Min}	Q_{Max}
14 bus		
1	0	10
2	-40	50
3	0	40
6	-6	24
8	-6	24

RESULTS AND DISCUSSION

Case study and results: For demonstrating the robustness, usefulness and applicability of the proposed algorithms (i.e., original PSO and CPSO) for solving complex and non-continuous problem, IEEE node-14 and-30 are utilized as a test system. Original PSO and CPSO algorithms are presented for solving reactive power optimization problem. These algorithms are presented and developed by MATLAB program. The load demand is changed from time to time, thus, in this study, utilize two type of loads (constant and variable load) so as to test the ability, effectiveness and feasibility of these algorithms for solving this problem at any change in load. For variable load, constant (active and reactive power) load demand at base case is multiplied by factor μ. And the load (active and reactive) demand is changing by utilizing equation as shown:

$$P_{Li} = \mu * P_{Li0} \tag{20}$$

$$Q_{Li} = \mu * Q_{Li0} \tag{21}$$

Where:

μ = The magnitude of the load variation ratio

P_{Li0}, Q_{Li0} = The initial (active and reactive) powers at load nodes

IEEE 14-node system: This system involves 20 branches, 5 generators, 1 reactive power VAR source compensation (capacitor banks) and 3 transformers; Bus, line, generator data, the bounds of reactive power (Q_G) for generators and other operating data. Table 1 shows constrains of independent variables while constrains of reactive power (Q_G) in MVAR for generators are given in Table 2.

This system has nine dimensions for the search space including 5 generator Voltages (V_G), 1 reactive power injected from capacitor bank (Q_C) and 3 transformer taps setting (Tap) as shown in Table 3 and 4. This system is utilized as a test system for two cases of load as follows:

Table 3: Simulation implications of IEEE node 14 systems at light loads

Control variables	Base case	CPSO	PSO	EP (Subbaraj and Rajnarayanan, 2009)	SARGA (Subbaraj and Rajnarayanan, 2009)
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
Reduction in P_L (%)	-	9.6	9.1	1.5	2.5
Total P_L (mW)	13.550	12.243	12.315	13.34620	13.21643

Table 4: Simulation implications of IEEE node 14 system at heavy loads

Control variables	Base case	CPSO	PSO
V_{G1}	1.060	1.100	1.100
V_{G2}	1.045	1.100	1.100
V_{G3}	1.010	1.050	1.010
V_{G6}	1.070	1.100	1.035
V_{G8}	1.090	1.100	1.100
Tap_{4-7}	0.978	1.025	1.001
Tap_{4-9}	0.969	0.975	1.005
Tap_{5-6}	0.932	1.025	1.007
Q_{C-9}	0.19	0.189	0.180
Reduction in P_L (%)	-	10.7	12.5
Total P_L (mW)	126.02	112.47	110.25

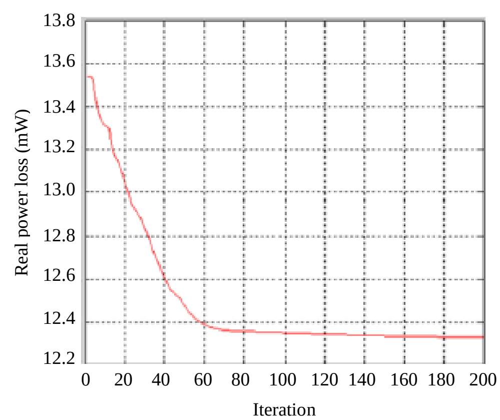

Fig. 2: Convergence for IEEE-14 node power system with original PSO algorithm at light loads

Case (1) at constant (light) load: This case is utilize IEEE node-14 as a test system at constant (light) loads (when μ = 1). In this case, the system loads, total generations and power losses in this case are: P_{load} = 259.0 MW and Q_{load} = 73.5 MVAR; P_G = 272.3 MW and Q_G = 82.4 MVAR; P_{loss} = 13.55 MW and Q_{loss} = 54.5 MVAR, respectively. The simulation results for this case and comparison with EP and SARGA algorithms (Subbaraj and Rajnarayanan, 2009) which are given in Table 3. Figure 2 and 3 illustrate

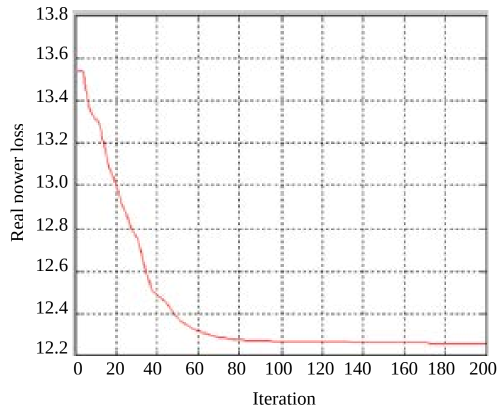

Fig. 3: Convergence for IEEE-14 node power system with CPSO algorithm at light loads

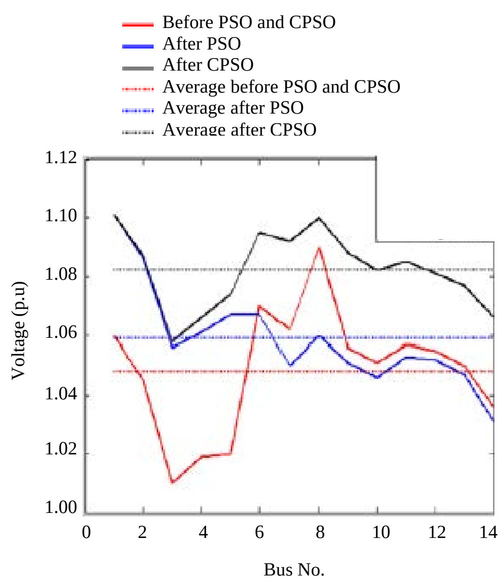

Fig. 4: Voltage profile for IEEE-14 node power system at light loads

the convergence characteristic of original PSO and CPSO algorithms, from these figures indicate that the convergence characteristic of CPSO best than original PSO, Fig. 4 shows the voltage profile for this case after and before original algorithms and from this figure, it is clear that the average voltage at initial is about 1.048 and at PSO is about 1.059 and at CPSO is about 1.082. The reduction in Power Losses (P_L) are 9.6% at CPSO, 9.1% at PSO, 1.5% at EP and 2.5% at SARGA algorithms. From the simulation implications indicate that CPSO algorithm has high ability and reliability in solving complex problem in power system than original PSO and other two algorithms in the literature.

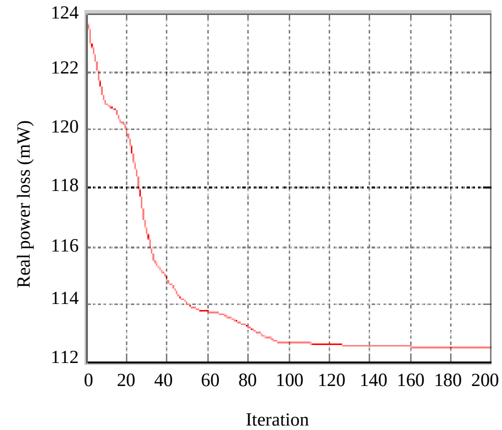

Fig. 5: Convergence for IEEE-14 node power system with original PSO algorithm at heavy loads

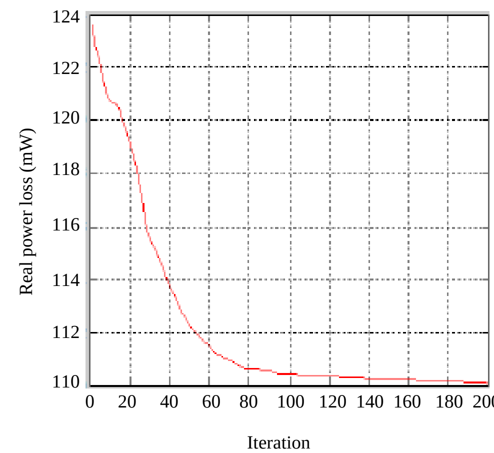

Fig. 6: Convergence for IEEE-14 node power system with CPSO algorithm at heavy loads

Case (2) at variable (heavy) load: This case is utilize IEEE node-14 as a test system at variables (heavy) loads (when μ = 2.5). In this case, the system loads, total generations and power losses in this case are: P_{load} = 668.2 mW and Q_{load} = 189.6 MVAR; P_G = 794.2 MW and Q_G= 641.9 MVAR; P_{loss} = 126.02 MW and Q_{loss}= 493.4 MVAR, respectively and there are 2V at node 4 and 14 outside the limits in the system and these voltages in pu are V_4 = 0.949 and V_{14} = 0.928. The simulation results for this case and comparison with original PSO algorithms which are given in Table 4. Figure 5 and 6 show the convergence characteristic of original PSO and CPSO algorithms, from these Figure indicate that the convergence characteristic of CPSO best than original PSO. Figure 7 shows the voltage profile for this case after and before original PSO and CPSO algorithms and from Fig. 7, it is clear that

Table 5: Control variables limits for IEEE 30 node system

IEEE bus-30/variables	Min	Max
30 bus		
Generator Voltage (V_G)	0.95	1.10
Transformer position (Tap)	0.90	1.00
VAR source compensation (Q_c)	0.00	0.20

Table 6: Constrains of reactive power generation for IEEE 30-node system

IEEE bus-30/generator nodes	Q_{Min}	Q_{Max}
30 bus		
1	0	10
2	-40	50
5	-40	40
8	-10	40
11	-6	24
13	-6	24

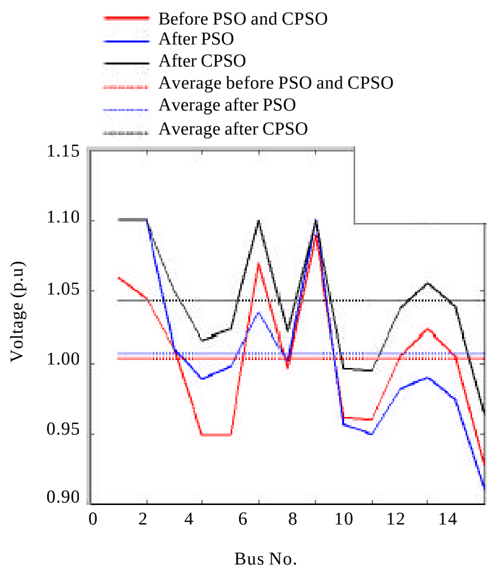

Fig. 7: Voltage profile for IEEE-14 node power system at heavy loads

the average voltage at initial is about 1.003 and at PSO is about 1.007 and at CPSO is about 1.043 and all voltages of the system are inside the limits after CPSO algorithm but V_{14} is still outside the limits after original PSO algorithm. The reduction in Power Losses (P_L) are 12.5% at CPSO, 10.7% at PSO algorithms. From the simulation implications indicate that CPSO algorithm has high ability and reliability in solving complex problem in power system than original PSO.

IEEE 30-node system: This system is utilized as another test system to evaluate efficiency of the presented algorithms. This system involves 6 generators at nodes (1, 2, 5, 8, 11 and 13), 2 reactive power (shunt capacitors) VAR sources at buses (10 and 24) and 4 transformers at branches). Bus, line, generator data, bounds of reactive power (Q_G) in MVAR for generators and other operating data were given in this system has 12 independent

Table 7: Simulation results of IEEE 30 node system at light load

Control variables	Base case	CPSO	PSO	EP (Subbaraj and Rajnarayanan, 2009)	SARGA (Subbaraj and Rajnarayanan, 2009)
V_{G1}	1.060	1.100	1.100	-	-
V_{G2}	1.045	1.086	1.072	1.097	1.094
V_{G5}	1.010	1.052	1.038	1.049	1.053
V_{G8}	1.010	1.059	1.048	1.033	1.059
V_{G1}	1.082	1.083	1.058	1.092	1.099
V_{G13}	1.071	1.100	1.080	1.091	1.099
Tap_{11}	0.978	1.008	0.987	1.01	0.99
Tap_{12}	0.969	0.993	1.015	1.03	1.03
Tap_{15}	0.932	1.024	1.009	1.07	0.98
Tap_{36}	0.968	0.987	1.012	0.99	0.96
Q_{C10}	0.19	0.077	0.077	0.19	0.19
Q_{C24}	0.043	0.123	0.128	0.04	0.04
Reduction in P_L (%)	-	8.7	7.4	6.6	8.3
Total P_L (mW)	17.55	16.01	16.25	16.38	16.09

Table 8: Simulation results of IEEE 30 node system at heavy load

Control variables	Base case	CPSO	PSO
V_{G1}	1.060	1.100	1.100
V_{G2}	1.045	1.089	1.086
V_{G5}	1.010	1.040	1.037
V_{G8}	1.010	1.049	1.047
V_{G11}	1.082	1.100	1.083
V_{G13}	1.071	1.100	1.089
Tap_{11}	0.978	1.004	0.990
Tap_{12}	0.969	0.982	0.986
Tap_{15}	0.932	1.017	1.025
Tap_{36}	0.968	0.975	0.990
Q_{C10}	0.19	0.105	0.104
Q_{C24}	0.043	0.162	0.157
Reduction in P_L (%)	-	10.1	10.5
Total P_L (mW)	50.07	45.00	44.78

(control) variables including 5 Generator Voltages (V_G), 2 injected reactive power from capacitors (Q_C) and 4 transformer Tap (Tap) as given in Table 5-8 and their constrains tabulated in Table 5 and the constrains of generator reactive power (Q_G) in MVAR are shown in the Table 6. This system is utilized as a test system for two cases of load as follows:

Case (1) at constant (light) load: In this case utilize IEEE node-30 as a test system at constant (light) load (when μ = 1). In this case, the system loads, total generations and power losses in this case are: P_{loss} = 283.9 MW and Q_{load} = 126.2 MVAR; P_G = 300.9 MW and Q_G = 133.9 MVAR; P_{loss} = 17.55 MW and Q_{loss} = 67.69 MVAR, respectively. The simulation results for this case and comparison also with EP and SARGA algorithms (Subbaraj and Rajnarayanan, 2009) which are given in Table 7. Figure 8 and 9 show the convergence characteristics of this system with original PSO and CPSO algorithms and from these figures clearly conclude that the CPSO algorithm is best and reaching optimal solution in less iterations than original PSO algorithm. Figure 10 shows the voltage profile of this system before and after

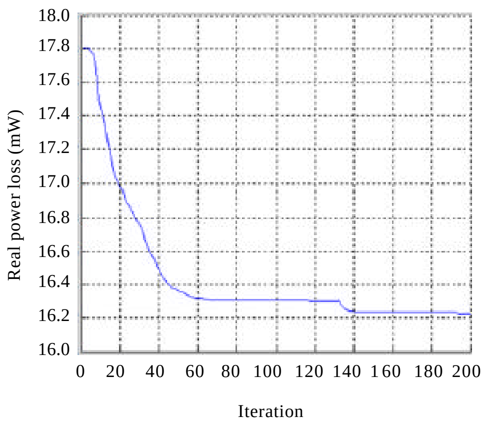

Fig. 8: Convergence of IEEE 30-node system with PSO algorithm at light load (Minimum real power loss)

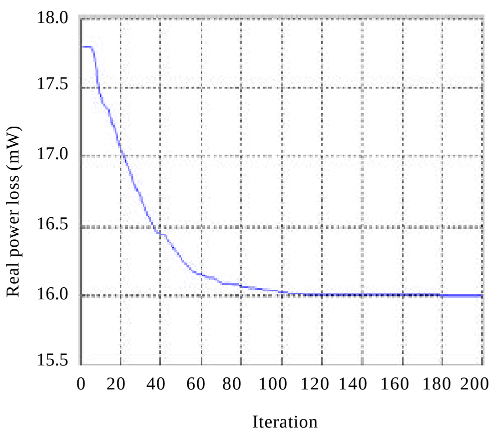

Fig. 9: Convergence of IEEE 30-node system with CPSO algorithm at light load (Minimum real power loss)

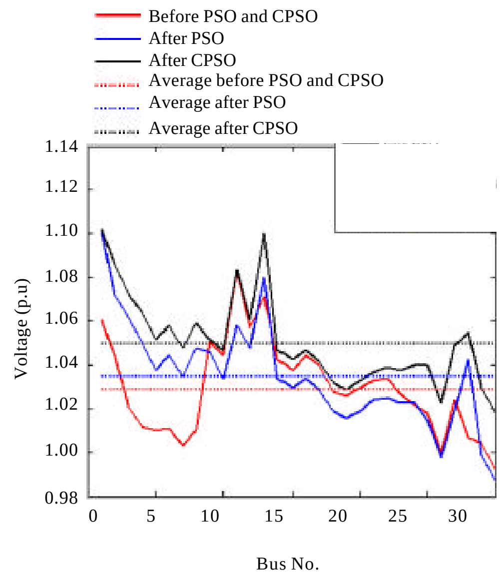

Fig. 10: Voltage profile of IEEE 30-node system at light load

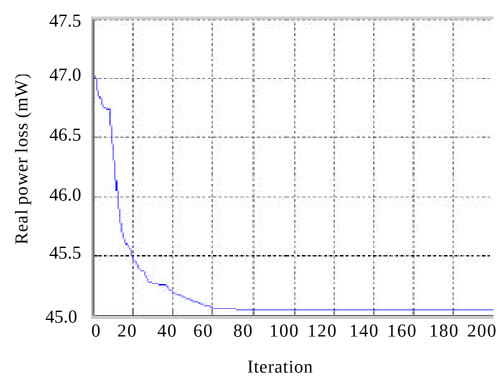

Fig. 11: Convergence of IEEE 30-node system with original PSO algorithm at heavy load (Minimum real power loss)

original PSO and CPSO algorithms and from this figure it is clear that the average voltage at initial is about 1.029 and at original PSO about 1.035 and at CPSO about 1.050. The reduction in Power Losses (P_L) are 8.7% at CPSO, 7.4% at PSO, 6.6% at EP and 8.3% at SARGA algorithms. From the simulation implications indicate that CPSO algorithm has high ability, efficiency and reach the optimal solution in lesser iterations in solving complex problem in power system than original PSO technique and other two algorithms in the literature.

Case (2) at variable (heavy) load: This case is utilize IEEE node-14 as a test system at variables (heavy) loads (when μ = 1.5). In this case the system loads, total generations and power losses in this case are: P_{load} = 444.9 MW and Q_{load} = 198.1 MVAR; P_G = 495.0 MW and Q_G= 331.0 MVAR; P_{loss} = 50.07 MW and Q_{loss} = 190.5 MVAR, respectively. In this system there are 3 voltages at nodes 26, 29 and 30, respectively, outside the limits and these Voltages in pu are V_{26} = 0.939, V_{29} = 0.949 and V_{30} = 0.930. From this case, conclude that the losses are increased when the load is increasing and the voltages are decreasing. The simulation results for this case and comparison with original PSO algorithms which are tabulated in Table 7. Figure 11 and 12 show the convergence characteristic for original PSO and CPSO algorithms, from these figures indicate that the convergence characteristic of CPSO best and reached the optimal solution in less iterations than original PSO. Figure 13 shows the voltage profile for this case after and before original PSO and CPSO algorithms and from this figure, it is clear that the average voltage at initial is about

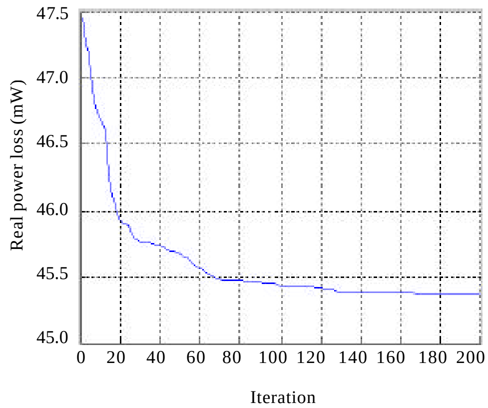

Fig. 12: Convergence of IEEE 30-node system with CPSO algorithm at heavy load

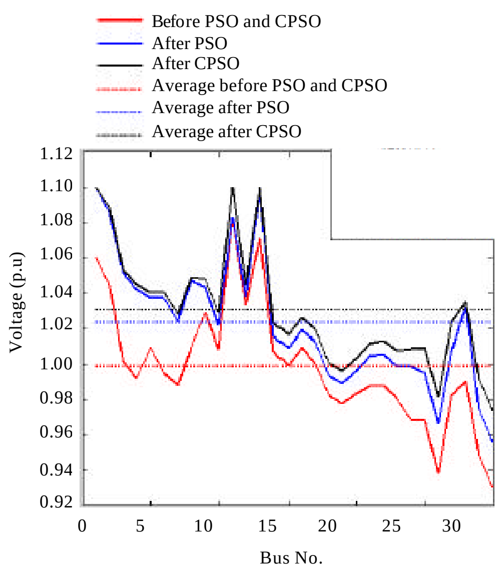

Fig. 13: Voltage profile of IEEE 30-node system at heavy load

0.999 and at PSO is about 1.023 and at CPSO is about 1.030 and all voltages of the system are inside the limits after CPSO and original PSO algorithms. The reduction in Power Losses (P_L) are 10.5% at CPSO, 10.1% at PSO algorithms. From the simulation implications indicate that CPSO algorithm has high ability and reliability in solving complex problem in power system than original PSO.

CONCLUSION

In this study, original PSO and CPSO algorithms are employed for solving reactive power optimization problem which is considered as non continous optimization problem with containing numbers of equality and inequality constrains. The goal of utilizing objective function are to decreasing of active Power Loss (P_L) and voltage profile enhancement of the power system through a proper control for the reactive power devices. In this study, the chaotic strategy merged with PSO algorithms in order to prevent plunge into the local minima at the premature convergence due to the high ability and ergodic of the chaos strategy than random search in original PSO technique and to get rapid convergence to the global solution. In order to evaluate and test these two algorithms, IEEE node and standard power systems are utilized as a test system. Also in this study employed two types of loads in order to test the proposed algorithms for solving this problem at any change in loads because the loads are variable from time to time and these two types of loads are: constant (light) load and variable (heavy) load and concluded that when the loads are increasing the losses also will increasing and the voltage will decreasing as discussed in the results. From simulation implications, proved that CPSO algorithm is best performance, high ability, high speed in convergence characteristic, also obtains lesser loss reduction with less number for iterations and obtains optimal settings of the independent variables than original PSO algorithm and other reported algorithms for light load and best than original PSO technique for heavy load. Also, the results indicate that CPSO algorithms has high flexibility, effective and robustness for solving complex and non-continuous problem in the power system and it is believed that CPSO will encouraging as algorithm for future research for displaying a fruitful implication.

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