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A Chaotic Particle Swarm Optimization (CPSO) Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract
This paper presents a chaotic particle swarm algorithm for solving the multi-objective reactive power dispatch problem. To deal with reactive power optimization problem, a chaotic particle swarm optimization (CPSO) is presented to avoid the premature convergence. By fusing with the ergodic and stochastic chaos, the novel algorithm explores the global optimum with the comprehensive learning strategy. The chaotic searching region can be adjusted adaptively. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and simulation results show that (CPSO) is more efficient than other algorithms in reducing the real power loss and maximization of voltage stability index.
Keywords:chaotic particle swarm optimization, Optimization, Swarm Intelligence, optimal reactive power, Transmission loss.

1.Introduction

One of the major problems faced by power system operators is the reactive power dispatch imposed on electric power utilities for a continuous and reliable supply of energy. Major power loads require a significant amount of reactive power that has to be supplied while maintaining load bus voltages within their permissible operating limits. In order to maintain desired levels of voltages and reactive flows under various operating conditions and system configurations, power system operators may utilize a number of control tools such as switching var sources, changing generator voltages, and by adjusting transformer tap settings. By an optimal adjustment of these controls, the redistribution of the reactive power would minimize transmission losses.Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method (O.Alsac et al.1973; Lee K Yet al.1985), Newton method (A.Monticelli et al.1987) and linear programming (Deeb Net al.1990; E. Hobson1980; K.Y Lee et al.1985; M.K. Mangoli 1993) .The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently Global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem (S.R.Paranjothi et al 2002;D. Devaraj et al 2005) . In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point (C.A. Canizareset al.1996). The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis is used as the indicator of voltage stability. In recent years, several new optimization techniques have emerged. The evolutionary algorithms (EAs) for reactive power optimization problem have been extensively studied. Several global optimization algorithms such as differential evolution (DE) (Dib.N et al .2010; Lin. C et al.2010), genetic algorithm (GA) (Zhang et al.2009 ; Vaitheeswaran.S et al.2008) , simulated annealing (SA) (Ferreira, J. A et al.1997), Ant colony optimization (ACO) (Hosseini.S. A et al 2008), particle swarm optimization (PSO) (Perez Lopez et al.2009; Liu, D et al.2009; Li, W.-T et al.2010 ; Goudos, S et al.2010 ; Shavit, R et al.2005) are used for reactive power optimization problem. However, these methods present certain drawbacks with the possibility of premature convergence to a local optimum. In this paper, a novel chaotic PSO algorithm (CPSO) is proposed. Based on the ergodicity, regularity and pseudo-randomness of the Chaotic variable, chaotic search is used to explore better solutions. The performance of (CPSO) has been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

2. Voltage Stability Evaluation

2.1 Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. The linearized steady state system power flow equations are given by.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{q\theta} & J_{QV}\end{bmatrix} \quad (1)$$

Where

ΔP = Incremental change in bus real power.

ΔQ = Incremental change in bus reactive Power injection

$\Delta\theta$ = incremental change in bus voltage angle.

ΔV = Incremental change in bus voltage Magnitude

$J_{p\theta}$, J_{PV} , $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q = \left[J_{QV} - J_{Q\theta} J_{P\theta^{-1}} J_{PV}\right]\Delta V = J_R \Delta V \quad (2)$$

$$\Delta V = J^{-1} - \Delta Q \quad (3)$$

Where

$$J_R = \left(J_{QV} - J_{Q\theta} J_{P\theta^{-1}} JPV\right) \quad (4)$$

J_R is called the reduced Jacobian matrix of the system.

2.2 Modes of Voltage instability

Voltage Stability characteristics of the system can be identified by computing the eigen values and eigen vectors

Let

$$J_R = \xi \wedge \eta \quad (5)$$

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R and

$$J_{R^{-1}} = \xi \wedge^{-1} \eta \quad (6)$$

From (3) and (6), we have

$$\Delta V = \xi \wedge^{-1} \eta \Delta Q \quad (7)$$

or

$$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q \quad (8)$$

Where ξ_i is the ith column right eigenvector and η the ith row left eigenvector of J_R.

λ_i is the ith eigen value of J_R.

The ith modal reactive power variation is,

$$\Delta Q_{mi} = K_i \xi_i \quad (9)$$

where,

$$K_i = \sum_j \xi_{ij^2} - 1 \quad (10)$$

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

$$\Delta V_{mi} = [1/\lambda_i]\Delta Q_{mi} \quad (11)$$

It is seen that, when the reactive power variation is along the direction of ξ_i the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the ith eigenvalue. In this sense, the magnitude of each eigenvalue λ_i determines the weakness of the corresponding modal voltage. The smaller the magnitude of λ_i, the weaker will be the corresponding modal voltage. If $|\lambda_i| = 0$ the ith modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let $\Delta Q = e_k$ where e_k has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\, \xi_1}{\lambda_1} \quad (12)$$

η_{1k} k th element of η_1

V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\, \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \quad (13)$$

3.Problem Formulation

The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

3.1Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (Ploss) in transmission lines of a power system. This is mathematically stated as follows.

$$P_{loss}= \sum_{\substack{k=1 \\ k=(i,j)}}^{n} g_{k}(V_i^2+V_j^2-2V_i V_j \cos\theta_{ij}) \qquad (14)$$

Where n is the number of transmission lines, g_k is the conductance of branch k, V_i and V_j are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

3.2 Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes (VD) at load buses. This is mathematically stated as follows.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \qquad (15)$$

Where nl is the number of load busses and V_k is the voltage magnitude at bus k.

3.3 System Constraints

Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \qquad (16)$$

$$Q_{Gi} - Q_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \qquad (17)$$

where, *nb* is the number of buses, P_G and Q_G are the real and reactive power of the generator, P_D and Q_D are the real and reactive load of the generator, and G_{ij} and B_{ij} are the mutual conductance and susceptance between bus *i* and bus *j*.Generator bus voltage (V_{Gi}) inequality constraint:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i \in ng \qquad (18)$$

Load bus voltage (*VLi*) inequality constraint:

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i \in nl \qquad (19)$$

Switchable reactive power compensations (*QCi*) inequality constraint:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i \in nc \qquad (20)$$

Reactive power generation (*QGi*) inequality constraint:

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i \in ng \qquad (21)$$

Transformers tap setting (T_i) inequality constraint:

$$T_i^{min} \le T_i \le T_i^{max}, i \in nt \qquad (22)$$

Transmission line flow (S_{Li}) inequality constraint:

$$S_{Li}^{min} \le S_{Li}^{max}, i \in nl \qquad (23)$$

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

4. Principle of CPSO

4.1Principle of CPSO

Inspired by the social behaviours of animal, bird flocking and fishing, PSO was developed by (Kennedy et al . 1995) . The particle is endowed with two factors: velocity and position which can be regarded as the potential solution in the *D* dimension problem space. In basic PSO, they can be updated by following formulas:

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 r_{1d}(P_{id}(t) - x_{id}(t)) + c_2 r_{2d}\left(P_{gd}(t) - x_{id}(t)\right) \qquad (24)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad (25)$$

Where i = 1,….., N, d = 1,…,D, N is the number of particles. ω is the inertia weight factor to control the exploration and exploitation. r_{1d} and r_{2d} are two random numbers within the range [0, 1]. $v_{id}(t)$ and $x_{id}(t)$ are the velocity and position of the current particle *i* at time step t in the dth-dimensional search space respectively. When $v_{id}(t)$ and $x_{id}(t)$ are beyond the boundary, the solution may be illegal. So, the treatment of boundaries in the PSO method is important in order to prevent the swarm from explosion (Xu.S et al .2007). In many practical problems, the search range x_{id} is in $[X_{min};X_{max}]D$. v_{id} should be clamped to a maximum magnitude V_{max}. p_i is the previous best position of particle *I* which is also called "personal best", and its *d*th-dimensional part is p_{id}. The global best" p_g is the best position found in the whole particles, and its *d*th-dimensional part is p_{gd}. c_1, c_2 are the acceleration constants which change the velocity of a particle towards the p_i and p_g.

4.2Modification Techniques in CPSO

The basic PSO uses p_g as neighbourhood topology. Each particle learns from its p_i and p_g. Restricting the social learning part to p_g can make basic PSO converge quickly. However, because all particles in the swarm learn from the p_g even if the current p_g is far from the global optimum, particles may easily be attracted to the area and trapped in a local optimum. Furthermore, the fitness value of a particle is determined by all dimensions. A particle that has discovered the region corresponding to the global optimum in some dimensions may have a low fitness value because of the poor solutions in other dimensions (Liang, J.-Jet al 2006) . In order to acquire more beneficial information from the entire swarm, we define p_c as "comprehensive best position".

$$p_c = \left\{\frac{\sum_{i=1}^{N} p_{i1}}{N}, \frac{\sum_{i=1}^{N} p_{i2}}{N}, \ldots, \frac{\sum_{i=1}^{N} p_{id}}{N}, \ldots, \frac{\sum_{i=1}^{N} p_{iD}}{N}\right\} \quad (26)$$

Where i = 1,..,N. Thus Equation (1) is modified as

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 r_{1d}\big(P_{id}(t) - x_{id}(t)\big) + c_2 r_{2d}\big(P_{cd}(t) - x_{id}(t)\big) \quad (27)$$

where p_{cd} is the dth-dimensional part of p_c. By using p_c instead of p_g, all particles' p_i can potentially be used as the exemplars to guide their flying direction. The comprehensive learning strategy yields a larger potential search space than that of the basic PSO. On the other hand, a particle can learn from p_g, as well as its personal best and the other particles' best, so that the particle can learn from particle itself, the elite and other particles. The strategy can increase the initial diversity and enable the swarm to overcome premature convergence problem. Basic PSO has shown some important advances by providing high speed of convergence in specific problems. However it does exhibit some shortages (Modares.H et al.2010). During the process of evolution, sometimes particles lose their abilities of exploration and will be stagnated. When some particles' velocity is be close to zero, other particles will quickly fly into the region near the inactive particles position that guided by p_i and p_g. Because of the particles randomicity in initialization and evolution process, the updating sometimes looks aimless. As a result, when p_g is trapped in a local optimum, the whole swarm becomes premature convergence, and the exploration performance will not be improved. Optimization algorithms based on the chaos theory are stochastic search methodologies that differ from any of the existing evolutionary algorithms. Due to the non-repetition of chaos, it can carry out overall exploration at higher velocities than stochastic and ergodic searches that depend on probabilities (Coelho, L. Det al.2009) . Chaotic PSO can be divided into two types. In the first type, chaos is embedded into the velocity updating equation of PSO. In (Modares.H et al.2010) , c_1 and c_2 are generated from the iterations of a chaotic map instead of using the rand function. In (Wang, Y., et al. 2010), a chaotic map is used to determine the value of ω during iterations. In the second type, chaotic search is fused with the procedures of PSO. This type is a kind of multi-phase optimization technique that chaotic optimization and PSO can switch to each other according to certain conditions (Wu.Q 2011) . Therefore, this paper provides a new strategy, which not only introduces chaotic mapping with certainty, ergodicity and stochastic property into PSO algorithm, but also proposes multi-phase optimization integrated by chaotic search and PSO evolution. The multi-phase optimization of chaotic PSO includes: v_{id} and x_{id} are updated by basic PSO with comprehensive learning strategy. If the swarm is stagnated, chaotic disturbance would be introduced. Here, variance σ^2 demonstrates the converge degree of all particles.

$$\sigma^2 = \sum_{i=1}^{N}\left[\left(f_i - f_{avg}\right)/f\right]^2 \quad (28)$$

$$f = max\left\{1, max\left\{\left|f_i - f_{avg}\right|\right\}\right\} \quad (29)$$

Where f_i is the fittness of the ith particle; $favg$ is the average fitness value; f is the factor of fitness value. The bigger σ^2 is the broader ith particles will spread. Otherwise, they will almost converge. The chaotic sequence can be generated by the logistic map introduced by Robert May in 1976. It is often cited as an example of how complex behaviour can arise from a simple dynamic system without any stochastic disturbance (He, Y.-Y., et al. 2009) The equation is the following

$$y_{id}(t+1) = \mu y_{id}(t)\big(1 - y_{id}(t)\big) \quad (30)$$

Where $y_{id}(t) \in (0,1), i = 1,..,N, d = 1,..,D. \mu$ is usually set to 4 obtain ergodicity of $y_{id}(t+1)\ within\ (0,1)$. When the initial value $y_{id}(0) \in \{0.25.0.5.0.75\}$ using equation (30) we can obtain chaotic sequences. In order to increase the population diversity and prevent premature convergence, we add adaptively chaotic disturbance P_c at the time of stagnation. Thus, $P_c\ is\ modified\ as\ P_c^{'}$.

$$p_{cd}'(t+1) = p_{cd}(t) + R_{id}\big(2_{yid}(t) - 1\big) \quad (31)$$

$$R_{id} = \beta\left|p_{cd}(t) - p_{id}(t)\right| \quad (32)$$

Where β is the region scale factor. Because$y_{id} \in (0,1)$, the second part of Equation (31) is in the range of $(-|R_{id}|, |R_{id}|)$ that would restrict the searching area around p_c. In addition, the searching range can be adaptively adjusted by the distance between p_i and p_c. If p_c is surrounded with the previous best positions pi, it means that a good region may have been found, and it is reasonable to search elaborately in a small area. On the contrary, if p_i is far from p_c, this probably suggests that a good area has not yet been found. For better solution,

searching region should be enlarged (Lin, C.et al.2007).
Thus in CPSO, the new position can be expressed as

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 r_{1d}\big(p_{id}(t) - x_{id}(t)\big) + c_2 r_{2d}\big(p'_{cd}(t) - x_{id}(t)\big) \quad (33)$$

Different from Equation (24), p_g is replaced by p'_c at the time of stagnation when σ^2 is less than the stagnation factor ξ. Chaotic search is restricted into a small range to obtain high performance in local exploration. Additionally, the algorithm keeps a dynamic balance between global and local searches due to its adaptive mechanism. With the new updating rule, different exemplars are used in different dimensions to explore a larger search space than the basic PSO. In addition, chaotic disturbance is embedded in different dimensions to maintain the diversity which plays an important role in avoiding early convergence.

5.Simulation Results

The validity of the proposed Algorithm technique is demonstrated on IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus.

Table 1. Voltage Stability under Contingency State

Sl.No	*Contigency*	*ORPD Setting*	*Vscrpd Setting*
1	28-27	0.1400	0.1422
2	4-12	0.1658	0.1662
3	1-3	0.1784	0.1754
4	2-4	0.2012	0.2032

Table 2. Limit Violation Checking Of State Variables

State variables	*limits*		*ORPD*	*VSCRPD*
	Lower	*upper*		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400
V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

Table 3. Comparison of Real Power Loss

Method	*Minimum loss*
Evolutionary programming[11]	5.0159
Genetic algorithm[12]	4.665
Real coded GA with Lindex as SVSM[13]	4.568
Real coded genetic algorithm[14]	4.5015
Proposed CPSO method	4.2031

6. Conclusion

A large-scale power system should supply power to the customers in a reliable and economic way while keeping system voltages in permissible limits. The purpose of the optimal reactive dispatch problem is to improve system voltage profile by minimizing power system losses. In this research paper a chaotic particle swarm has been utilized to sole the optimal reactive power dispatch problem. The performance of the proposed algorithm has been tested in standard IEEE test system and simulation results shows the best performance of the proposed system and the real power loss has been considerably reduced .

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