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Rapid Particle Swarm Optimization Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract

In this paper Rapid Particle Swarm Optimization (RPSO) algorithm is proposed to solve the optimal reactive power dispatch Problem. The Rapid Particle swarm Optimization (RPSO) algorithm is obtained by merging PSO with Cauchy mutation. Basic idea is to introduce the Cauchy mutation into PSO such that it prevents PSO from trapping into a local optimum through stretched jumps made by the Cauchy mutation. In order to evaluate the efficiency of the proposed algorithm, it has been tested on IEEE 30 bus system and compared other standard algorithms. Results show's that RPSO is more efficient in reducing the real power loss and voltage index also improved

***Keywords**: rapid particle swarm optimization, cauchy mutation, optimal reactive power, transmission loss*

1. Introduction

In recent years the optimal reactive power dispatch (ORPD) problem has received great attention as a result of the improvement on economy and security of power system operation. Solutions of ORPD problem aim to minimize object functions such as fuel cost, power system loses, etc. while satisfying a number of constraints like limits of bus voltages, tap settings of transformers, reactive and active power of power resources and transmission lines and a number of controllable Variables [1, 2]. In the literature, many methods for solving the ORPD problem have been done up to now. At the beginning, several classical methods such as gradient based [3], interior point [4], linear programming [5] and quadratic programming [6] have been successfully used in order to solve the ORPD problem. However, these methods have some disadvantages in the Process of solving the complex ORPD problem. Drawbacks of these algorithms can be declared insecure convergence properties, long execution time, and algorithmic complexity. Besides, the solution can be trapped in local minima [1, 7]. In order to overcome these disadvantages, researches have successfully applied evolutionary and heuristic algorithms such as Genetic Algorithm (GA) [2], Differential Evolution (DE) [8] and Particle Swarm Optimization (PSO) [9]. It is reported in those that evolutionary or heuristic algorithms are more efficient than classical algorithms for solving the reactive power problem. During the last decades a lot of population-based Meta heuristic algorithms were proposed. Voltage stability evaluation using modal analysis [10] is used as the indicator of voltage stability. In the recent decades a number of optimization algorithms based on natural phenomena have been developed. Particle Swarm Optimization (PSO) [11-18] is motivated from the social behaviour of organisms, such as bird flocking and fish schooling. In order to prevent PSO from falling in a local optimum, a Rapid PSO (RPSO) is proposed by integrating a Cauchy mutation operator. Because the expectation of Cauchy distribution does not exist, the variance of Cauchy distribution is infinite. Some researches [19-20] have indicated that the Cauchy mutation operator is good at the global search for its long jump ability. Besides the Cauchy mutation, RPSO chooses the natural selection strategy of evolutionary algorithms as the basic elimination strategy of particles. RPSO combines PSO with Cauchy mutation and evolutionary selection strategy. It has the fast convergence speed characteristic of PSO, and greatly overcomes the tendency of trapping into local optima of PSO.The performance of RPSO 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.

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2. Voltage Stability Evaluation

2.1. Modal analysis for voltage stability evaluation

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

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

where :

ΔP = Incremental change in bus real power.
ΔQ = Incremental change in bus reactive Power injection
Δθ = incremental change in bus voltage angle.
ΔV = Incremental change in bus voltage Magnitude

Jpθ , JPV , JQθ , JQV jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. To reduce (1), let ΔP = 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 have been identified by computing the Eigen values and Eigen vectors.

Let

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

where,

ξ = right eigenvector matrix of JR
η = left eigenvector matrix of JR
∧ = diagonal eigenvalue matrix of JR and

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

From (5) and (8), 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 ξi is the ith column right eigenvector and η the ith row left eigenvector of JR. λi is the ith Eigen value of JR. 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

ξji is the jth element of ξi

The corresponding ith modal voltage variation is

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

If | λi | =0 then the ith modal voltage will collapse .

In (10), let ΔQ = ek where ek 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 is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

3.1. Minimization of Real Power Loss

Minimization of the real power loss (Ploss) in transmission lines is mathematically stated as follows.

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

where n is the number of transmission lines, gk is the conductance of branch k, Vi and Vj 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

Minimization of the voltage deviation magnitudes (VD) at load buses is mathematically stated as follows.

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

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

3.3. System Constraints

Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

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

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

where, nb is the number of buses, PG and QG are the real and reactive power of the generator, PD and QD are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (VGi) inequality constraint:

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

Load bus voltage (VLi) inequality constraint:

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

Switchable reactive power compensations (QCi) inequality constraint:

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

Reactive power generation (QGi) inequality constraint:

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

Transformers tap setting (Ti) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \quad (22)$$

Transmission line flow (SLi) inequality constraint:

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

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

4. Particle Swarm Optimization (PSO)

Particle Swarm Optimization Algorithm (PSO) is a population based optimization tool, where the system is initialized with a population of random particles and the algorithm searches for optima by updating generations. Suppose that the search space is D-dimensional. The position of the i-th particle can be represented by a D-dimensional vector $X_i = (x_{i1}, x_{i2}, .., x_{iD})$ and the velocity of this particle is $V_i = (v_{i1}, v_{i2}, .., v_{iD})$.The best previously visited position of the i-th particle is represented by $P_i = (p_{i1}, p_{i2}, .., p_{iD})$ and the global best position of the swarm found so far is denoted by $P_g = (p_{g1}, p_{g2}, .., p_{gD})$. The fitness of each particle can be evaluated through putting its position into a designated objective function. The particle's velocity and its new position are updated as follows:

$$v_{id}^{t+1} = \omega^t v_{id}^t + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_2 r_2^t (p_{gd}^t - x_{id}^t) \quad (24)$$

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

where $d \in \{1,2, .., D\}, i \in \{1,2, .., N\}$ N is the population size, the superscript t denotes the iteration number, ω is the inertia weight, r1 and r2 are two random values in the range [0,1], c1 and c2 are the cognitive and social scaling parameters which are positive constants.

5. Cauchy Mutation Merged into PSO

From the mathematic theoretical analysis of the trajectory of a PSO particle [21-23], the trajectory of a particle Xid converges to a weighted mean of Pid and Pgd. Whenever the particle converges, it will “fly” to the personal best position and the global best particle’s position. According to the update equation, the personal best position of the particle will gradually move closer to the global best position. Therefore, all the particles will converge onto the global best particle’s position. This information sharing mechanism makes PSO have a very fast speed of convergence. Meanwhile, because of this mechanism, PSO can’t guarantee to find the global minimal value of a function. In fact, the particles usually converge to local optima. Without loss of generality, only function minimization is discussed here. Once the particles trap into a local optimum, in which Pid can be assumed to be the same as Pgd, all the particles converge on Pgd. At this condition, the velocity update equation becomes:

$$V'_{id} = \omega V_{id} \quad (26)$$

When the iteration in the equation (26) goes to infinite, the velocity of the particle Vid will be close to 0 because of 0≤ ω <1. After that, the position of the particle Xid will not change, so that PSO has no capability of jumping out of the local optimum. It is the reason that PSO often fails on finding the global minimal value. To overcome the weakness of PSO discussed at the beginning of this section, the Cauchy mutation is incorporated into PSO algorithm. The basic idea is that, the velocity and positions of a particle are updated not only according to (24) and (25), but also according to Cauchy mutation as follows:

$$V'_{id} = V_{id}\exp(\delta) \quad (27)$$

$$X'_{id} = X_{id} + V'_{id}\delta_{id} \quad (28)$$

where δ and δid denote Cauchy random numbers since the expectation of Cauchy distribution doesn't exist, the variance of Cauchy distribution is infinite so that Cauchy mutation could make a particle have a long jump. By adding the update equations of (27) and (28), RPSO greatly increases the probability of escaping from the local optimum. In standard PSO, the position of a particle is updated according to equations (24) and (25). That is, for each particle there is nowhere to move but following the direction of the best particle and the flying direction is nearly determinate through the generation. From the above analysis of PSO, the particles incline to converge on a local optimum.

5.1. Natural Selection Strategy

In the standard PSO, all particles are directly updated by their offspring no matter whether they are improved. If a particle moves to a better position, it can be replaced by the updated. However if it moves to a worse position, it is still replaced by its offspring. In fact, the most particles fly to worse positions for most cases; therefore the whole swarm will converge on local optima. Like evolutionary algorithms, RPSO introduces an evolutionary selection strategy in which each particle survives according to a natural selection rule. Therefore, the particle's position at the next step is not only due to the position update but also the evolutionary selection. Such strategy could greatly reduce the probability of trapping into local optimum. The evolutionary selection strategy is carried out as follows. Assume the size of the swarm is m, pair-wise comparison over the union of parents and offspring (1,2,…2m) is made. For each particle, q opponents are randomly chosen from all parents and offspring with equal probability. If the fitness of particle i is less than its opponent, it will receive a "win". Then select m particles that have the more winnings to be the next generation.

The detail of the selection framework is as follows:

a. Step1: For each particle of parent and offspring, assign win[i]=0.
b. Step2: Randomly select q particles (opponents) for each particle in parent and offspring.
c. Step3: For each particle, compare it with its q opponents. For particle i, if the fitness of its opponent j is larger than particle i , then win[i]++.
d. Step4: Select m particles that have the more winnings to be the next generation.

RPSO Algorithm for solving reactive power dispatch problem

1. Produce the preliminary particles by arbitrarily producing the position and velocity for each particle.
2. Appraise each particle's fitness.
3. For each particle, if its fitness is smaller than its previous best(P_{id}) fitness, update P_{id} .
4. For each particle, if its fitness is smaller than the best one (P_{gd}) of all the particles, update *Pgd*.
5. For each particle, do
    a) Engender a new particle *t* according to the formula (24) and (25).
    b) Engender a new particle *t'* according to the formula (27) and (28).
    c) Compare *t* with *t'* chose the one with smaller fitness to be the offspring.
6. Produce the next generation according to the above evolutionary selection strategy.
7. If end criterion is satisfied, then stop, otherwise go to 3.

6. Simulation Results

The efficiency of the proposed Rapid Particle Swarm Optimization (RPSO) is demonstrated by testing it on standard 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. The simulation results have been presented in Tables 1, 2, 3 &4. And in the Table 5 shows the proposed algorithm powerfully reduces the real power losses when compared to other given algorithms. The optimal values of the control variables along with the minimum loss obtained are given in Table 1. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table 1. Results of RPSO – ORPD optimal control variables

Control variables	Variable setting
V1	1.048
V2	1.045
V5	1.042
V8	1.030
V11	1.003
V13	1.032
T11	1.00
T12	1.00
T15	1.01
T36	1.01
Qc10	3
Qc12	3
Qc15	2
Qc17	0
Qc20	2
Qc23	3
Qc24	3
Qc29	2
Real power loss	4.2858
SVSM	0.2471

Optimal Reactive Power Dispatch problem together with voltage stability constraint problem was handled in this case as a multi-objective optimization problem where both power loss and maximum voltage stability margin of the system were optimized simultaneously. Table 2 indicates the optimal values of these control variables. Also it is found that there are no limit violations of the state variables. It indicates the voltage stability index has increased from 0.2471 to 0.2486, an advance in the system voltage stability. To determine the voltage security of the system, contingency analysis was conducted using the control variable setting obtained in case 1 and case 2. The Eigen values equivalents to the four critical contingencies are given in Table 3. From this result it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

Table 2. Results of RPSO -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	Variable Setting
V1	1.048
V2	1.046
V5	1.045
V8	1.031
V11	1.004
V13	1.033
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	3
Qc15	2
Qc17	3
Qc20	0
Qc23	2
Qc24	2
Qc29	3
Real power loss	4.9899
SVSM	0.2486

Table 3. Voltage Stability under Contingency State

Sl.No	Contingency	ORPD Setting	VSCRPD Setting
1	28-27	0.1419	0.1434
2	4-12	0.1642	0.1650
3	1-3	0.1761	0.1772
4	2-4	0.2022	0.2043

Table 4. Limit Violation Checking Of State Variables

State variables	limits Lower	upper	ORPD	VSCRPD
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 5. Comparison of Real Power Loss

Method	Minimum loss
Evolutionary programming [24]	5.0159
Genetic algorithm [25]	4.665
Real coded GA with Lindex as SVSM [26]	4.568
Real coded genetic algorithm [27]	4.5015
Proposed RPSO method	4.2858

7. Conclusion

In this paper, one of the recently developed Rapid Particle Swarm Optimization (RPSO) has been applied to solve optimal reactive power dispatch problem. Different objective functions have been utilized to minimize real power loss and the voltage profile has been improved. Projected RPSO approach has been tested on the IEEE 30-bus power system & simulation results indicate the effectiveness and robustness of the proposed RPSO algorithm in solving optimal reactive power dispatch problem.

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