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

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Abstract— This paper presents a quantum behaved particle swarm algorithm for solving the multi-objective reactive power dispatch problem .Particle swarm optimization (PSO) is a population-based swarm intellect algorithm that share various similarities with evolutionary computation methods. Yet, PSO is determined by the imitation of a societal psychosomatic metaphor aggravated by cooperative behaviours of bird and other societal organisms instead of, the endurance of the fittest individual. Stimulated by the traditional PSO method and quantum procedure theories, this work presents a new Quantum behaved PSO (QPSO). The simulation results reveal high-quality performance of the QPSO in solving an optimal reactive power dispatch problem. In order to appraise the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms.

Index Terms— Quantum Behaved PSO; Optimization; Swarm Intelligence; Optimal Reactive Power; Transmission Loss

I. INTRODUCTION

Optimal reactive power dispatch problem is one of the complex problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The reactive power dispatch problem involve most excellent utilization of the existing generator bus voltage magnitudes, transformer tap setting and the productivity of reactive power sources so as to curtail the real power loss and to augment the voltage stability of the system. Various statistical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1, 2], Newton method [3] and linear programming [4-7]. Universal Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8.9]. In recent years, the problem of voltage stability and voltage collapse has become a key concern in power system planning and operation. To improve the voltage stability, voltage magnitudes alone will not be a dependable indicator of how far an operating point is from the collapse point. Therefore, 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 assessment using modal analysis [10] is used as the indicator of voltage stability. The field of swarm intellect is a rising research area that presents features of self-organization and cooperation principles among group members bio-inspired on social insect societies [11–13]. The particle swarm optimization (PSO) initially developed by Kennedy and Eberhart in 1995 [14, 15] is a population based swarm algorithm. Likewise to genetic algorithms [16], an evolutionary algorithm approach PSO is an optimization utensil based on a population, where each member is seen as a particle, and each particle is a probable solution to the problem under investigation. Newly, the concepts of quantum mechanics and physics have aggravated the generation of optimization methods [17–21]. Enthused by the PSO [31,32] and quantum mechanics theories, this work presents a new Quantum-behaved PSO (QPSO) approach. The performance of (QPSO) 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. Section IV & V describe about the classical PSO and Quantum PSO. Finally section VI describe about the simulation study of the proposed algorithm application to optimal reactive power dispatch problem.

II. VOLTAGE STABILITY EVALUATION

A. Modal analysis for voltage stability evaluation

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.

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

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

Where

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

J_R is called the reduced Jacobian matrix of the system.

B. Modes of Voltage instability:

Voltage Stability characteristics of the system can be recognized 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 Eigen value 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 i_{th} row left eigenvector of J_R.

λ_i is the ith Eigen value of J_R.

The i_{th} 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 j_{th} element of ξ_i

The corresponding ith modal voltage variation is

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

In (8), let $\Delta Q = e_k$ where e_k has all its elements zero except the k_{th} 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

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

III. Problem Formulation

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

A. Minimization of Real Power Loss

Minimization of the real power loss (Ploss) in transmission lines of a power system 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.

B. Minimization of Voltage Deviation

Minimization of the Deviations in voltage 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.

C. System Constraints

Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

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

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

where, nb is the number of buses, P_G and Q_G are the real and reactive power of the generator, PD and QD 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:

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

Load bus voltage (V_{Li}) inequality constraint:

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

Switchable reactive power compensations (Q_{Ci}) inequality constraint:

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

Reactive power generation (Q_{Gi}) inequality constraint:

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

Transformers tap setting (T_i) inequality constraint:

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

Transmission line flow (S_{Li}) 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.

IV. Classical Particle Swarm Optimization

The primary point of developing PSO is the swap over of information between creatures of the same species and offers some class of evolutionary benefit.

The method for implementing the global version of PSO is given by the following steps:

Step 1. Initialization of swarm position and velocity.

Step 2. Estimate of particle's fitness.

Step 3. Comparison to pbest (personal best).

Step 4. Comparison to gbest (global best):.

Step 5. Update of every particle's velocity and position: Modify the velocity, v_i, and position of the particle, x_i, according to Eqs. (24) and (25):

$$v_i(t+1) = w.v_i(t) + c_1.ud.[p_i(t) - x_i(t)] + c_2.ud.[p_g(t) - x_i(t)] \quad (24)$$

$$x_i(t+1) = x_i(t) + \Delta t.v_i(t+1) \quad (25)$$

Where w is the inertia weight; i = 1,2,. . . ,N indicates the number of particles of population (swarm);

t = 1, 2,. . . t_{max} indicates the iterations, w is a parameter called the inertia weight; $v_i = [v_{i1}, v_{i2}, \ldots, v_{in}]^T$ stands for the velocity of the i_{th} particle, $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T$ stands for the position of the ith particle of population, and $p_i = [p_{i1}, p_{i2}, \ldots, p_{in}]^T$ represents the best previous position of the ith particle. Positive constants c_1 and c_2 are the cognitive and social components, respectively, which are the acceleration constants responsible for varying the particle velocity towards p_{best} and g_{best}, respectively. Index g represents the index of the best particle among all the particles in the swarm. Variables u_d and u_d are two random functions in the range [0, 1]. Eq. (25) represents the position update, according to its previous position and its velocity, considering $\Delta t = 1$.

Step 6. Repeating the evolutionary cycle: Return to Step 2 until a stop criterion has been reached.

V. Quantum-Behaved Particle Swarm Optimization

In classical procedure, a particle is depicted by its position vector x_i and velocity vector v_i, which decide the trajectory of the particle. The particle moves along a determined trajectory in Newtonian procedure, but this is not the case in quantum mechanics. In quantum theory, the word trajectory is worthless, because x_i and v_i of a particle cannot be determined concurrently according to ambiguity principle. Therefore, if individual particles in a PSO system have quantum behavior, the PSO algorithm is bound to work in an unusual fashion [22, 23]. The quantum model PSO called here as QPSO, the position of a particle is depicted by wave function Ψ (x, t) (Schrodinger equation) [18, 25], instead of position and velocity. The dynamic behavior of the particle is extensively divergent form that of that the particle in classical PSO systems in that the exact values of x_i and v_i cannot be determined concurrently. In this background, the probability of the particle's appearing in position x_i from probability density function $|\Psi(x,t)|^2$, the shape of which depends on the potential field the particle lies in [24].Employing the Monte Carlo process, the particles shift according to the following iterative equation [22–26]:

$$\begin{cases} x_i(t+1) = P + \beta.|Mbest_i - x_i(t)|.\ln(l/u) \text{if } k \geq 0.5 \\ x_i(t+1) = P - \beta.|Mbest_i - x_i(t)|\ln(l/u) \text{if } k < 0.5 \end{cases} \quad (26)$$

Where β is a design parameter called contraction-expansion coefficient [23]; u and k are values generated according to a uniform probability distribution in range [0, 1]. The comprehensive point called majority thought or Mean Best (M_{best}) of the population is defined as the mean of the p_{best} positions of all particles and it given by

$$Mbest = \frac{1}{N} \sum_{d=1}^{N} P_{g,d}(t) \quad (27)$$

Where g represents the index of the best particle among all the particles in the swarm. In this case, the local attractor [26] to promise convergence of the PSO presents the following coordinates:

$$P = \left(c_1 P_{i1d} + c_2 P_{g1d}\right)/(c_1 + c_2) \quad (28)$$

The process for implementing the QPSO is given by the following steps:

Step 1. Initialization of swarm positions

Step 2. Evaluation of particle's fitness

Step 3. Comparison to p_{best} (personal best).

Step 4. Comparison to g_{best} (global best).

Step 5. Update the global point- Calculate the M_{best} .

Step 6. Update the particles' position: Change the position of the particles where c_1 and c_2 are two random numbers generated using a uniform probability distribution in the range [0, 1].

Step 7. Repeat the evolutionary cycle: Loop to Step 2 until a stop criterion is reached.

VI. 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. The simulation results have been presented in Tables 1, 2, 3 &4. And in the table 5 shows clearly that proposed algorithm efficiently 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. Equivalent to this control variable setting and it was found that there are no limit violations in any of the state variables.

Table 1. Results of QPSO – ORPD optimal control variables

Control variables	Variable setting
V1	1.040
V2	1.041
V5	1.033
V8	1.031
V11	1.010
V13	1.041
T11	1.04
T12	1.01
T15	1.0
T36	1.0
Qc10	3
Qc12	3
Qc15	3
Qc17	0
Qc20	4
Qc23	3
Qc24	4
Qc29	3
Real power loss	4.4002
SVSM	0.2478

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 0.2478 to 0.2489, 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 QPSO -Voltage Stability Control Reactive Power Dispatch Optimal control variables

Control Variables	Variable Setting
V1	1.043
V2	1.043
V5	1.034
V8	1.033
V11	1.010
V13	1.034
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	4
Qc12	2
Qc15	4
Qc17	3
Qc20	0
Qc23	3
Qc24	2
Qc29	4
Real power loss	4.9851
SVSM	0.2489

Table 3. Voltage Stability under Contingency State

Sl.No	Contigency	ORPD Setting	VSCRPD Setting
1	28-27	0.1400	0.1420
2	4-12	0.1648	0.1662
3	1-3	0.1774	0.1762
4	2-4	0.2022	0.2032

Table 4. 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

State variables	limits		limits	VSCRPD
	Lower	Lower		
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[27]	5.0159
Genetic algorithm[28]	4.665
Real coded GA with Lindex as SVSM[29]	4.568
Real coded genetic algorithm[30]	4.5015
Proposed QPSO	4.4002

VII. CONCLUSION

In this research paper QPSO algorithm successfully solved optimal reactive power dispatch problem by reducing the real power loss and enhancing the volatge stability index.The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a high-quality performance for voltage stability Enhancement of large, complex power system networks. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system.

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