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An Enhanced Quantum-Behaved Particle Swarm Optimization for Security Constrained Economic Dispatch

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***Abstract*—QPSO algorithm has been widely used in economic dispatch of power system. However, the algorithm is often trapped in local optima because of lack of population diversity in the evolutionary process. Therefore, an operation called random perturbation is introduced into QPSO algorithm, which provides the algorithm with effective dynamic adaptability and improves the local search capabilities and global search capability. The improved algorithm is used in two groups of typical examples. And the optimization results were compared with GA algorithm, PSO algorithm and QPSO algorithm. The experimental results show that the new algorithm has better convergence and stability, obtains lower generation cost, and can effectively solve the power system economic dispatch problem.**

Keywords- economic dispatch; random perturbation; QPSO; population diversity

I. INTRODUCTION

Optimization algorithm has a wide range of applications in manufacturing, telecommunications, transportation, energy, and many other industrial engineering fields. It improves the effectiveness and operating efficiency of industrial systems through the optimization of specific problems. With the continuous improvement of environmental protection requirements and pollutant discharge standards, there are many hot issues that need to be resolved in the energy industry. The economic dispatch (ED) problem of power system is a typical optimization problem in power system planning and design and operation scheduling. The purpose of the system is to minimize the cost of generation subject to relevant system constraints[1].

Solving this problem has good application prospects and practical implications, many groups do research on this issue. The classic methods to solve this problem are: Lambda iteration method, gradient method, Newton method, dynamic programming and other methods . However, these numerical methods have disadvantages such as low computational efficiency and vulnerability to curse of dimensionality. With the deepening of research on swarm intelligence and bionic algorithms, the ED problem presents discrete, high-dimensional, nonlinear, multi-constraint and other characteristics can be better resolved. Genetic algorithm (GA) [2-4], particle swarm optimization (PSO) [5,6], Quantum-Behaved Particle Swarm Optimization (QPSO) [7] and other algorithms have been successfully applied in ED problems. Bakirtzis et al. applied GA and its improved algorithm to the ED problem and obtained better experimental results than dynamic programming [2]. Chen et al. proposed the adoption of a new coding method in the GA algorithm and comprehensively considered the constraints such as network loss and power exclusion zone. Based on this, GA was successfully applied to large-scale ED problems [3]. Gaing et al. successfully applied the PSO algorithm to the ED solution, and achieved better calculation results and computational efficiency than the GA algorithm [5]. Pancholi et al. used a variable penalty coefficient strategy to accelerate the iterative process of the PSO algorithm and achieved higher convergence accuracy than the basic PSO algorithm [6]. Sun et al. applied the QPSO algorithm to the solution of the ED problem and obtained better results than the PSO algorithm on three test cases [7].

In the process of evolution of QPSO algorithm, the initial convergence is fast, but the late particles tend to be concentrated in a specific location or in a few specific locations, resulting in the loss of the diversity of the group, and the search ability of the algorithm is greatly reduced. Therefore, this paper proposes a random perturbation QPSO (RP-QPSO) algorithm to introduce random perturbation strategies in the iterative optimization process, which can adaptively adjust according to search dynamics to increase group diversity. Relevant experimental research shows that RP-QPSO algorithm is suitable for solving large-scale, multi-constrained ED problems, with strong global search ability and robustness.

II. PROBLEM DESCRIPTION

The ED problem is an optimization problem that determines the power output of each effective bus to satisfy the system load demand, system network loss, upper and lower power constraints of each generator set, which will result in a least cost system state, so as to minimize the total power generation cost of the system.

A. ED Problem Formulation

The objective of the ED problem is to minimize the total system cost C, the objective function is[3,5]:

$$C = \min\left(\sum_{i=1}^{N_g} F_i(P_{Gi})\right), \quad i = 1,2,...N_g \tag{1}$$

where $F_i(P_{Gi})$ is the cost function of the ith generating unit, P_{Gi} is the real output of the ith unit, and N_g is the number of units in the system.

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The total system cost function of each generate unit is related to the actual power injected to the system, and is typically modeled by a smooth quadratic function as:

$$F_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2,\ i = 1,2,...N_g \tag{2}$$

where a_i, b_i and c_i are the cost coefficients of the ith generating unit.

The sum of power generated by all units in the system includes the total of the total demand power of the load in the system and the network loss. The power generated by each unit should be between its maximum output power and minimum output power, that is:

$$\sum_{i=1}^{N_g} P_{Gi} = P_D + P_L$$
$$P_{Gi}^{\min} < P_{Gi} < P_{Gi}^{\max}\ \ \mathrm{i} = 1,2,...N_g \tag{3}$$

where $\sum_{i=1}^{N_g} P_{Gi}$ is the total system generation, P_D is the total system load demand, P_L is the transmission losses.

B. System Transmission Losses

The most popular approach for finding an approximate value of the losses is by way of Kron's loss formula as follow, which represents the losses as a function of the output level of the system generate unit[3,5]:

$$P_L = \sum_{i=1}^{N_G} \sum_{j=1}^{N_g} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_g} P_{Gi} B_{i0} + B_{00} \tag{4}$$

where B_{ij}, B_{i0}, B_{00} are known the loss coefficient method or the B- coefficient method.

C. Prohibited operating zone

For a unit, due to the inherent physical characteristics of the generator, only the output power can only be in the inherent areas. Those areas that are between the maximum and minimum output power range but cannot be output are called prohibited zone. Taking into account the factor of the unit's power exclusion zone, the feasible operating zones can be described as follows[3,5]:

$$P_i^{\min} \le P_i \le P_{i,1}^l$$
$$P_{i,j-1}^u \le P_i \le P_{i,j}^l,\ j = 2,3,...,n_i \tag{5}$$
$$P_{i,n}^u \le P_i \le P_i^{\max}$$

where P_i is the real output of the *i*th generating unit, *j* is the *j*th range of the *i* unit.

III. Overview of the RP-QPSO optimization algorithm

The PSO algorithm is a kind of intelligence algorithm motivated by the behavior of bird populations. The main idea is to consider each particle as a particle with no weight and volume in the n-dimensional search space and to fly in the search space at a certain speed[8, 9]. Quantum-behaved Particle Swarm Optimization (QPSO) algorithm, the search space and solution space of the problem are two spaces of different, and the search space of an individual particle at each iteration is the whole feasible solution space of the problem, the experiment in results Sun's paper indicate that the QPSO works better than standard PSO on several benchmark functions[10, 11].

In the evolution of QPSO algorithm, each particle depends on two major factors: 1. the stochastic point of the best position of the particle and the best position of the total particle group; 2. the difference between the global optimal position of the particle and the previous experience of the particle. It is through the sharing of the group's advantage information and the excavation of its own experience and advantage information gap that the algorithm continuously evolves within the entire search space to find the optimal solution. In the QPSO algorithm, with the continuous evolution of particles, all particles tend to be concentrated in a specific location or in a few specific locations, the population diversity will inevitably decrease, and the algorithm will easily fall into the local optimal solution. Based on the QPSO evolutionary model, a random perturbation operation *p* is introduced. At each late stage of evolution, each particle in the population is perturbed with a random probability. The particle can be based on its own best position and the entire best particle. The gap information of the optimal location of the group is used to adjust its own behavior, so that the algorithm has a dynamic self-adaptation, which improves the global search ability of the algorithm and enhances the diversity of the group. During random perturbation, the particle position is updated by a parameter *r*, where *r* is a random number between 0 and 1. When it is less than or equal to the perturbation probability, the particle position is updated according to the perturbation step size. When it is greater than the perturbation probability, the particle position remains unchanged.

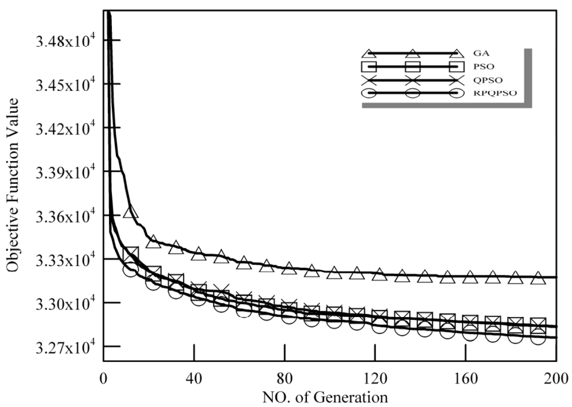
IV. Case and Analysis

A. 15-Unit system

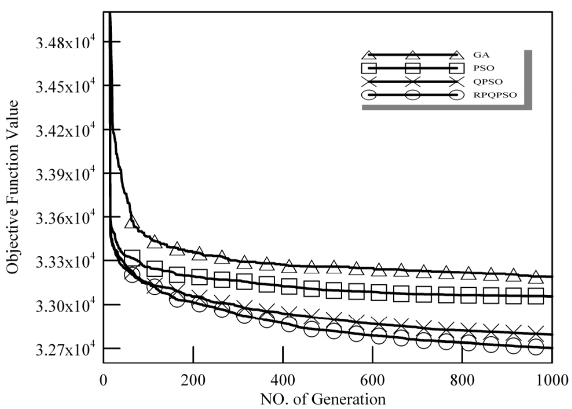
The 15-Unit system contains 15 thermal units. The power consumption of the entire system is 2630 MW. Table 1 gives the mean, optimum, worst value, and standard deviation of 50 experimental results. Figure 1 shows the convergence of each algorithm during evolution.

TABLE I. 15-Unit System Algorithm Experiment Results

Algorithm	Average	Best	Worst	SD
m=100, MAXITER=200				
GA	33071.18	32828.60	33217.85	94.9301
PSO	32833.51	32597.27	33169.21	131.5179
QPSO	32817.94	32663.55	33099.52	77.5130
RPQPSO	32712.86	32578.45	32978.93	77.3842
m=20, MAXITER=1000				
GA	33119.78	32891.71	33401.15	93.4492
PSO	33050.43	32607.51	33663.98	269.2847
QPSO	32787.11	32623.45	32973.11	86.6031
RPQPSO	32700.83	32570.03	33023.83	83.7899

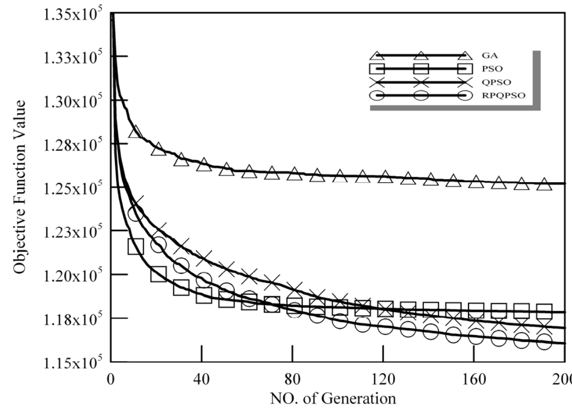


(a) m=100, MAXITER=200

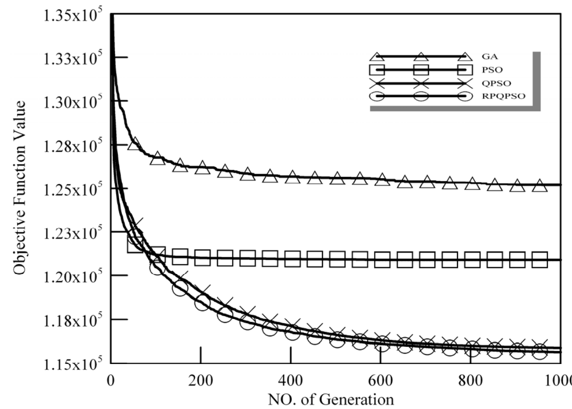


(b) m=20, MAXITER=1000

Figure1. The convergence of the 15-Unit system algorithm



(a) m=100, MAXITER=200



(b) m=20, MAXITER=1000

Figure 2. The convergence of the 15-Unit system algorithm

B. 40-Unit system

The 40-Unit system contains 40 thermal units and the total system power requirement is 8550 MW. The system is based on the actual Taipower system abstraction, which includes coal, electricity, fuel, gas and other different types of generators. Table 2 gives the mean, optimum, worst value, and standard deviation of 50 experimental results. Figure 2 shows the convergence of each algorithm during evolution.

TABLE II. 40-UNIT SYSTEM ALGORITHM EXPERIMENT RESULTS

Algorithm	**Average**	**Best**	**Worst**	**SD**
m=100, MAXITER=200				
GA	124467.7	122357.4	126360.5	966.4606
PSO	117864.0	115883.2	120379.9	1141.762
QPSO	116897.1	116102.2	117668.8	328.9184
RPQPSO	116039.7	115630.6	116596.7	262.8861
m=20, MAXITER=1000				
GA	124432.2	122357.5	126429.5	1022.536
PSO	120517.1	116919.9	124489.2	1648.844
QPSO	115889.2	115536.4	116825.2	274.9799
RPQPSO	115640.2	115313.1	116649.6	295.1661

C. Analysis and discussion

From the experimental results of Table 1, Table 2, RP-QPSO algorithm to solve the ED problem, relative to the GA algorithm, the optimal value, the average has greatly improved, the algorithm has good evolutionary search capabilities, and GA algorithm in In the evolution process, binary encoding/decoding is needed. It takes a long time and RP-QPSO algorithm has advantages in computation time. Compared to PSO algorithm, RP-QPSO algorithm has obvious advantages in average value and standard deviation, and the algorithm has high stability; RP-QPSO algorithm is in standard QPSO. Based on the algorithm, the perturbation factor is introduced, and then according to certain search mechanism requirements, a better solution is found. From the experimental results shown in Table 1 and Table 2, the RP-QPSO algorithm can obtain better optimal solutions and averages than the standard QPSO. As a result, it is proved that RPQPSO algorithm has stronger evolutionary search capability, the standard deviation of the two algorithms is close, and it has good robustness of the algorithm.

The convergence curves shown in Figure 1 and Figure 2 are the average results of 50 independent experiments for each group. From Figure 1 and Figure 2, it can be concluded that the PSO algorithm has a strong search ability in the early stages of the evolution process, but it is followed by premature convergence into local conditions. Optimal. The QPSO/RP-QPSO algorithm can gradually approach the global optimal solution with the increase of the number of evolution, and the RP-QPSO is superior to the QPSO algorithm in the experimental average.

V. Conclusion

This paper adds random perturbation operation based on QPSO algorithm, proposes RPQPSO algorithm, and applies RPQPSO to the solution of ED problem, and carries out multiple independence by using 15-unit and 40-unit systems with larger unit size. Experiments have achieved a better system cost based on satisfying the system power demand, and the standard deviation of experimental results is small, and the algorithm has good robustness. In the calculation process, the actual conditions such as unit power limitation, power exclusion zone and network loss have been comprehensively considered. The algorithm can be applied to the actual dispatch of the power system, reduce the power generation cost and energy consumption, and contribute to energy conservation and emission reduction.

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