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Research Article

Solving Power Economic Dispatch Problem with a Novel Quantum-Behaved Particle Swarm Optimization Algorithm

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This paper proposes the shrink Gaussian distribution quantum-behaved optimization (SG-QPSO) algorithm to solve economic dispatch (ED) problems from the power systems area. By shrinking the Gaussian probability distribution near the learning inclination point of each particle iteratively, SG-QPSO maintains a strong global search capability at the beginning and strengthen its local search capability gradually. In this way, SG-QPSO improves the weak local search ability of QPSO and meets the needs of solving the ED optimization problem at different stages. The performance of the SG-QPSO algorithm was obtained by evaluating three different power systems containing many nonlinear features such as the ramp rate limits, prohibited operating zones, and nonsmooth cost functions and compared with other existing optimization algorithms in terms of solution quality, convergence, and robustness. Experimental results show that the SG-QPSO algorithm outperforms any other evaluated optimization algorithms in solving ED problems.

1. Introduction

Solving economic dispatch (ED) problem is to ensure that the power production is safe, high-quality and meets the customer's electricity demand by using various technical and management measures to make the power production equipment in the best working state and reach the lowest cost of the power system. Simultaneously, the nonlinear characteristics of the generator, such as ramp rate limit, prohibited operating area, and nonsmooth cost function, should be considered. Therefore, the ED problem is a complex nonlinear problem with many constraints.

Traditionally, the ED problem can be solved by various mathematical programming methods, including lambda iterative method, the base point [1], the interior point method [2], the gradient method [3], and the dynamic programming method [4]. However, these deterministic numerical methods do not work effectively for problems with hard constraints such as nonsmooth and nonconvex cost functions, or suffer "dimensional disasters." Therefore, in order to effectively address the issues of the nonlinear characteristics of practical power systems, many swarm intelligence algorithms or evolutionary algorithms are used to solve multiconstrained optimization problems, including genetic algorithms (GA) [5], particle swarm optimization (PSO) [6], differential evolution (DE) [7], evolutionary programming (EP) [8, 9], tabu search (TS) [10], neural network (NN) [11, 12], ant colony search algorithm (ACSA) [13], artificial immune system (AIS) [14, 15], honey bee colony algorithm [16], firefly algorithm [17], and the hybrid method [18].

Besides, some improved algorithms are proposed. For example, Kaboli proposes an artificial cooperative search (ACS) [19] optimization algorithm, which is provided by balancing exploration of the problem's search space and exploitation of better results through the use of two advanced evolutionary operators and only one control parameter. Pandey proposes an improved FWA with Chaotic Sequence Operator (IFWA-CSO) [20], in which the global search ability of FWA has been strengthened. Sun uses the improved particle swarm optimization algorithm RDPSO (Random Drift Particle Swarm Optimization) to solve the power optimization problem [21]. In order to improve the local search capability of PSO, KHAMSAWANG and Grag adopt a hybrid method of differential evolution or genetic algorithm to enhance the local capability [22, 23]. Besides, Khan et al. control the diversity of particle swarm to avoid the algorithm falling into the local optimal [24–26]. Besides, other improved algorithms such as the iterated-based optimization method [27], dynamically controlled particle swarm optimization method [28] are also performed well on ED problems.

However, for these methods, the major deficiencies still are highly sensitive to the initial value of the control parameters and a large number of control parameters or some situations such as trap into local optima and premature easily occur. Therefore, it is difficult to obtain satisfactory and feasible solutions for multiconstrained, nonlinear optimization problems. The quantum-behaved particle swarm optimization (QPSO) algorithm is a variant PSO algorithm that has strong and robust global search ability but has relatively low convergence speed and local search ability.

Therefore, this paper proposes a shrink Gaussian distribution quantum-behaved optimization (SG-QPSO) algorithm to solve ED problems from the power systems area. By shrinking the Gaussian probability distribution near the learning inclination point of each particle iteratively, SG-QPSO not only maintains a strong global search capability at the early search stage but also strengthens the local search capability at the later stage. In this way, the proposed SG-QPSO improves the weak local search ability of QPSO and meets the needs of solving the ED optimization problem at different stages. Besides, SG-QPSO has fewer parameters than other optimization algorithms, such as genetic algorithms, differential evolution, or other one-dimensional search algorithms like the Powell algorithm, which is easier to control.

The remaining chapters of this paper are arranged as follows: Section 2 describes the proposed SG-QPSO in detail. Section 3 describes the mathematical formulation of the ED problem in detail. Section 4 shows the experimental results obtained by SG-QPSO on three power systems, compares its results with previous algorithms, and analyzes its merits and disadvantages. Section 5 summarizes this article and introduces the focus of future work.

2. The Proposed Algorithm

In this section, we first introduce the theoretical aspect of the canonical QPSO algorithm and then analyze its advantages and disadvantages when dealing with ED problems. Based on the analysis above, an improved QPSO algorithm called SG-QPSO is proposed, and its process of solving the ED problem is given as a flowchart.

2.1. QPSO Algorithm. The crucial issue of QPSO is how to design a reasonable potential energy field [29]. Clerc analyzed the dynamic evolution process and showed that each particle gradually converges to a point [30]. In other words, those points attract the particles swarm during the search process. Those points are named learning inclination points (LIPs) in QPSO, and its current position is calculated as follows:

$$p_{i,t}^{j} = \varphi_{i,t}^{j} \cdot P_{i,t}^{j} + \left(1 - \varphi_{i,t}^{j}\right) G_{t}^{j}, \tag{1}$$

where $\varphi_{i,t}^{j} \in (0,1)$ is a random variable generated by uniform distribution, $P_{i,t}^{j}$ is the value that denotes the j-th dimension of the current personal best position of particle i, and G_{t}^{j} represents the value of the jth dimension of the current global best position.

The updated formulation of each particle in QPSO is as follows:

$$X_{i,t+1}^{j} = p_{i,t}^{j} \pm 0.5 \cdot L_{i,t}^{j} \cdot \ln\left(\frac{1}{u_{i,t+1}^{j}}\right), \tag{2}$$

where $u_{i,t}^{j} \in (0,1)$ is a random variable generated by uniform distribution, $L_{i,t}^{j}$ is the length between the current position of each particle and the mean personal best position, and its definition is as follows:

$$\begin{aligned} L_{i,t}^{j} &= 2 \cdot \alpha_t \cdot \left|C_t^{j} - X_{i,t}^{j}\right|, \\ \alpha_t &= \alpha_0 + \left(\alpha_1 - \alpha_0\right) \cdot \frac{T-t}{T}. \end{aligned} \tag{3}$$

The mean personal best position is calculated by the following:

$$C_t^{j} = \sum_{1}^{M} P_{i,t}^{j}. \tag{4}$$

By simulating the strong uncertainty of the superposition of states in the quantum system, QPSO makes it possible to cover the whole probability search space during the search process. Simultaneously, the algorithm uses the mean personal best position to guide the particles to gradually aggregate to LIPs. This delay strategy makes the algorithm convergence slowly and helps the algorithms enhance their global search ability. The details of the QPSO algorithm can be found in [29].

2.2. The SG-QPSO Algorithm. When the area near the global or local optima is tiny, particles in QPSO are easier to skip this area for the range of update area of each particle is large. At the same time, considering that Gaussian distribution is introduced to generate random variables sequence may weaken the global search ability, a shrink Gaussian distribution quantum-behaved particle swarm optimization (SG-QPSO). In SG-QPSO, the variance of Gaussian distribution declines linearly to shrink the area of each particle near its LIP, which enhances the local search ability gradually and maintains the global search ability of QPSO during the search process. The update formula of the SG-QPSO algorithm is as follows:

$$\begin{cases} X_{i,t+1}^{j} = p_{i,t}^{j} + \left|C_t^{j} - X_{i,t}^{j}\right| \cdot \ln\left(\dfrac{1}{N_{i,t+1}^{j}(0,\sigma)}\right), & \text{if } k < 0.5, \\ X_{i,t+1}^{j} = p_{i,t}^{j} - \left|C_t^{j} - X_{i,t}^{j}\right| \cdot \ln\left(\dfrac{1}{N_{i,t+1}^{j}(0,\sigma)}\right), & \text{otherwise}, \end{cases} \tag{5}$$

where k is random values generated by using the uniform probability distribution functions in the range [0, 1]. The learning inclination point p and mean personal best position C is calculated by equations (1) and (4). Note that the number of particles in a particle swarm is M:

$$\sigma_t = \sigma_0 + (\sigma_1 - \sigma_0)\cdot\frac{T-t}{T}. \quad (6)$$

In equation (6), σ denotes the variance of Gaussian distribution, declining linearly from the initial value σ_1 and the end value σ_0 in the search process. T is the maximum number of fitness evaluations and t represents the current iteration step. The Pseudocode of the SG-QPSO algorithm is shown in Algorithm 1.

3. Solving ED Problem with SG-QPSO

3.1. Mathematical Model of Power System Economic Dispatch. The ED problem can be reduced to an optimization problem. Its goal is to determine the power output level of the online generator and further minimize the total fuel cost of all generators within a period while satisfying various nonlinear constraints.

3.1.1. Objective Function. The objective function of ED problem can be defined as follows:

$$\text{minimize}\, F_{\text{cost}} = \sum_{j=1}^{N_g} F_j(P_j), \quad (7)$$

where $F_j(P_j)$ is the cost function of jth generator set, P_j Is the actual output of the jth generator set, and N_g is the total number of generators in the power system.

The cost function of each generator set is related to the actual power put into the system and is usually modeled with a smooth quadratic function:

$$F_j(P_j) = a_j + b_jP_j + c_jP_j^2. \quad (8)$$

a_j, b_j, and c_j is the cost correlation coefficient of the jth generator set.

3.1.2. Constrains of ED Problem. In this work, we consider the following constraints of the ED problem:

(a) Power balance constraints

The power balance constraints are expressed as follows:

$$\sum_{j=1}^{N_g} P_j = P_D + P_L. \quad (9)$$

The total power generation of the system is equal to the load demand of the system plus transmission loss. In other words, the total power generation $\sum_{j=1}^{N_g} P_j$ should be equal to the total power demand P_D plus transmission network loss P_L while minimizing total power generation costs. P_L is usually approximated by the Krone loss formula, which represents the relationship between the transmission loss and the output level of the system generator set:

$$P_L = \sum_{j=1}^{N_g}\sum_{k=1}^{N_g} P_jB_{jk}P_k + \sum_{j=1}^{N_g} P_jB_{j0} + B_{00}, \quad (10)$$

where $1 \le j,k \le N_g$ the number of generators in the generator set, B_{j0}, B_{jk}, B_{00} is called loss coefficient. B_{jk} is a $N_g \times N_g$ matrix.

(b) Inequality constraints

$$P_j^{\min} < P_j < P_j^{\max}, \quad (j = 1, 2, \ldots, N_g). \quad (11)$$

According to the design requirements of the generator, the amount of power generated by each unit must vary between its minimum $P_j^{\min}$ and maximum $P_j^{\max}$ production limits.

(c) Ramp rate limitation

During the actual operation of the generator set, the operating range of all online units is limited by their ramp rate limitation. According to [5], the inequality constraint due to the slope limitation is as follows:

(i) If the amount of power generation increases

$$P_j - P_j^0 \le UR_j, \quad (12)$$

(ii) If the amount of power generation decreases

$$P_j^0 - P_j \le DR_j, \quad (13)$$

(d) Prohibited operating areas

Since the steam valve operates in the bearing (i.e., vibration), the system contains some prohibited operating zones. In the actual power system, the load demand of the power system must avoid prohibited zones. Therefore, if the constraints in (11) are considered, the feasible operating area of the jth generator set can be described in the following way:

$$\begin{aligned} P_j^{\min} &\le P_j \le P_{j,1}^l, \\ P_{j,k-1}^u \le P_j \le P_{j,k}^l, &\quad k = 2, 3, \ldots, n_j, \\ P_{j,n_j}^u &\le P_j \le P_j^{\max}, \end{aligned} \quad (14)$$

where $P_{j,k}^l$ and $P_{j,k}^u$ is The upper and lower boundaries of the kth prohibited zone of the jth generator set, n_j is the number of prohibited zones of the jth generator set.

3.1.3. The Mathematical Formulation of ED Problem. Combining the equations (11)–(13), we obtained the following:

$$\text{Max}(P_j^{\min}, P_j - DR_j) \le P_j \le \min(P_j^{\max}, P_j^0 + UR_j). \quad (15)$$

Therefore, considering the feasible operation zones, we can express the ED problem as the following constrained optimization problem:

$$\begin{aligned}
&\text{minimize } F_{\text{cost}} = \sum_{j=1}^{N} F_j(P_j) \\
&\text{subject to} \\
&\sum_{j=1}^{N_g} P_j = P_D + P_L \\
&\max\left(P_j^{\min}, P_j - DR_j\right) \le P_j \le P_{j,1}^{l} \\
&P_{j,k-1}^{u} \le P_j \le P_{j,k}^{l}, \ k = 2, 3, \ldots, n_j \\
&P_{j,n_j}^{u} \le P_j \le \min\left(P_j^{\max}, P_j^{0} + UR_j\right).
\end{aligned} \tag{16}$$

3.2. Solving ED Problem Using SG-QPSO. Before applying the SG-QPSO algorithm to the ED problem, make the following provisions:

Each component in a single particle represents a generation unit, so each particle represents a candidate solution for a given ED problem. The current position of the *t*th particle $P_{g,i}$ with N_g generation units can be given by the following:

$$P_{g,i} = \left[P_{i,1}, P_{i,1}, P_{i,2}, \ldots, P_{i,N_g}\right], \quad i = 1, 2, \ldots, M, \tag{17}$$

where M is the population size, which is the index to generate *j*th unit, and P is the output power of the *i*th generating unit in the *j*th particle.

3.2.1. Objective Function and Constraint Handling. The equality constraints in the formula can be handled by adding penalty terms. The objective function becomes as follows:

$$\text{minimize } F = \sum_{j=1}^{N} F_j(P_j) + K_n \left| \sum_{j=1}^{N} P_j - P_D - P_L \right|, \tag{18}$$

where K_n is called the penalty coefficient and is a positive real number, which increases with the number of iterations. The penalty term in equation (18) is the equality constraint in equation (9). When the ED problem is restricted, it is solved by a population-based search method (such as SG-QPSO). If the equality constraint is violated, the value of the penalty term is nonzero.

On the one hand, when the candidate solution violates the equation-constrained candidate solution, equation (18) gives a larger objective function value so that the candidate solution has a greater probability of being discarded. On the other hand, when the equality constraint is not violated, the penalty term is zero. No matter how large the penalty coefficient is, the final penalty term value is zero. Therefore, the final objective function value is obtained by adding the value of the penalty term to the given objective function value so as to control each candidate solution in the population to approach the feasible solution area.

4. Experiments

4.1. The Summary of Three Power Systems. Three real power systems are used to verify the effectiveness of SG-QPSO, with considering the ramp rate limit and the prohibited zones. Other optimization methods are also tested on these three systems for comprehensive performance comparison, including binary-coded GA [5], PSO with inertial weights [6], DE [7], Ant Colony Search Algorithm (ACSA) [13], artificial immune system (AIS) [14], bee colony optimization (BCO) [16], firefly algorithm (FA) [17], standard PSO (SPSO) with shrinkage and inertial weights [31], chaotic PSO (CPSO) [32], antipredatory PSO (APSO) [33], mixed gradient descent PSO (HGPSO) [31], mixed PSO with mutation (HPSOM) [31], QPSO [29], and GQPSO [34]; the Hopfield neural network (NN) was also tested. Note that, for each system, all test methods use the same objective function.

System 1: the system consists of 6 thermal units, 26 bus bars, and 46 transmission lines. The load demand is 1263 MW. The characteristics of the 6 thermal units are given in Tables 1 and 2. In the normal operation of the system, the loss factor with a basic capacity of 100 MVA is shown in Table 3. It is a small system and is the easiest problem among three test systems, and the dimension of the ED problem is 6. As shown in Table 2, there are 12 prohibited zones in this system, and 13 inequality constraints are generated according to these prohibited zones.

System 2: this system has 15 thermal units, the characteristics of which are given in Tables 4 and 5. The load demand of the system is 2630 MW. Due to space constraints, the loss coefficient matrix is not listed. This system is a medium-scale system, and its ED problem has 15 dimensions. As shown in Table 5, the power generating units 2, 5, 6, and 12 have 11 prohibited zones. Therefore, according to the inequality constraints described above regarding its ED problem, the ED problem of this system is relatively difficult to optimize compared with System 1.

System 3: the system contains 40 units in a large-scale hybrid power generation system named Tai power system. The load demand of the system is 8550 MW. Due to space constraints, unit parameters and loss factors are not listed. The dimension of the ED problem of this system is 40. In the ED problem of this system, each power generation unit has no prohibited zone, so there are fewer unequal constraints, but this does not significantly reduce the difficulty of the problem. The large size and multiple fuel options attribute of this system make the ED problem to be one of the most difficult to solve among the three systems.

4.2. Parameters Setting. For each of these three systems, the maximum number of iterations to execute the objective

Input: Input parameters: σ_1 and σ_0
Output: Fitness value of EDPs
Step 1: Initialize the current position of each particle, and set its personal best position to be its current position;
Step 2: Set $t = 0$;
Step 3: While the termination condition is not met, perform the following steps;
Step 4: Set $t = t+1$ and compute the mean best position C_t^i;
Step 5: From $i = 1$ executes the following steps;
Step 6: Evaluate the value of X, and update G_t and P_t^i;
Step 7: Update position of each particle according to (2);
Step 8: set $i = i+1$, and return to Setp 5 until $i = M$;
Step 9: Return to Step 3;
Step 10: Return result

Algorithm 1: The pseudocode of SG-QPSO algorithm.

Table 1: 6 units of power generation capacity and coefficient.

Unit	$P_j^{\min}$	$P_j^{\max}$	a_j	b_j	c_j
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	220	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Table 2: Slope limit and prohibited zones of the generator set 6-unit system.

Unit	P_j^0	UR_j	DR_j	Prohibited zones
1	440	80	120	[210, 240][350, 380]
2	170	50	90	[90, 110][140, 160]
3	200	65	100	[150, 170][210, 240]
4	150	50	90	[80, 90][110, 120]
5	190	50	90	[90, 110][140, 150]
6	110	50	90	[75, 85][100, 105]

Table 3: Loss factor b of 6-unit system.

B_{ij}	1	2	3	4	5	6
1	0.0017	0.0012	0.0007	−0.0001	−0.0005	−0.0002
2	0.0012	0.0014	0.0009	0.0001	−0.0006	−0.0001
3	0.0007	0.0009	0.0031	0	−0.001	−0.0006
4	−0.0001	0.0001	0	0.0024	−0.0006	−0.0008
5	−0.0005	−0.0006	−0.001	−0.0006	0.0129	−0.0002
6	−0.0002	−0.0001	−0.0006	−0.0008	−0.0002	0.0150
B_{0i}	−0.0004	−0.0001	0.0007	0.0001	0.0002	−0.0007
B_{00}			0.056			

function of each optimization algorithm is set to 20,000. Simultaneously, two sets of experiments are performed on each system for each algorithm. One has a population size of $M = 100$ and a maximum number of generation of $G_{\max} = 200$, another population size of $M = 20$ and $G_{\max} = 1000$. On each system, each algorithm performed 100 independent experiments with a given maximum generation $G_{\max}$ and population size M. The penalty coefficient in the objective function is set to $K_t = 100\sqrt{t}$, where t is the current number of generations.

The other experimental configuration settings are as follows: The size of the crossover probability $p_c = 0.8$, and the size of the mutation probability $p_m = 0.1$ in GA; the constant mutation factor used by the DE algorithm is $f_m = 0.4$, and the size of the crossover rate is $\mathrm{CR} = 0.8$; for PSO with inertia weight, the inertia weight decreases linearly from 0.9 to 0.4 during the search process, the acceleration coefficients $c_1 = c_2 = 2.0$ and $V_{\max} = ((P_j^{\max} - P_j^{\min})/2)$; for SG-QPSO, during the search process, the variance of the Gaussian distribution σ decreases linearly from 5 to 0.001.

TABLE 4: Slope limit and prohibited zones of the generator set 15-unit system.

Unit	P_j^{min}	P_j^{max}	a_j	b_j	c_j
1	150	455	671	10.1	0.000299
2	150	455	574	10.2	0.000183
3	20	130	374	8.8	0.001126
4	20	130	374	8.8	0.001126
5	150	470	461	10.4	0.000205
6	135	460	630	10.1	0.000301
	135	465	548	9.8	0.000364
8	60	300	227	11.2	0.000338
9	25	162	173	11.2	0.000807
10	25	160	175	10.7	0.001203
11	20	80	186	10.2	0.003586
12	20	80	230	9.9	0.005513
13	25	85	225	13.1	0.000371
14	15	55	309	12.1	0.001929
15	15	55	323	12.4	0.004447

TABLE 5: Slope limitation and prohibition zone for the 15-unit system of the generator set.

Unit	P_j^0	UR_j	DR_j	Prohibited zones
1	400	80	120	
2	300	80	120	[185, 225][305, 335][420, 450]
3	105	130	130	
4	100	130	130	
5	90	80	120	[180, 200][305, 335][390, 420]
6	400	80	120	[230, 255][365, 395][430, 455]
7	350	80	120	
8	95	65	100	
9	105	60	100	
10	110	60	100	
11	60	80	80	
12	40	80	80	[30, 40][55, 65]
13	30	80	80	
14	20	55	55	
15	20	55	55	

The algorithm parameters of ACSA, BCO, AIS, and FA are set according to the corresponding literature. The parameter configuration of other PSO variables, namely SPSO, CPSO, APSO, HGPSO, HPSOM, QPSO, and GQPSO, is the same as the parameters suggested in the literature. The parameter setting of Hopfield NN is consistent with that in literature.

4.3. Experiment Results and Analysis. Table 6 lists the total cost of each method for the ED problem of System 1. From Table 6, the average cost and standard deviation of 100 runs of SG-QPSO are better than other methods, which shows that the performance and robustness of SG-QPSO on System 1 is better than other algorithms. Under the two experimental configurations, the CPSO algorithm is the second best method of the system in terms of the mean cost. When $M = 100$ and $G_{max} = 200$, the worst performance optimization algorithm is APSO, and the mean cost obtained in 100 runs is 15473.3164$/h. For this system, Hopfield NN produces the worst results. When $M = 20$ and $G_{max} = 1000$, the mean cost of SPSO performs the worst, although the lowest cost found in 100 runs is 15442.9130 $/h, which is better than other comparison algorithms other than SG-QPSO. When $M = 100$ and $G_{max} = 200$, the SG-QPSO algorithm obtained the best solution, the lowest standard deviation, and the best mean cost.

Table 7 lists the solution vector P_j ($j = 1, 2, \ldots, 6$) relative to the best solution. The minimum cost of SG-QPSO running 100 times is 15442.7831 $/h when $M = 100$ and $G_{max} = 200$. To prove that the equality constraints in (16) are satisfied, we add the power loss (12.4173 MW) to the load demand (1263 MW) for a total of 1275.4173 MW. By comparing the sum to the total power output (1276.4183 MW), we can find that the equality constraints (i.e., power balance constraints) are well satisfied. Figure 1 visualizes the convergence of all test methods on the ED problem of System 1 for an average of 100 experiments, indicating that SG-QPSO has better convergence than other algorithms.

Table 8 lists the mean cost, minimum and maximum cost, and the standard deviation values obtained by performing 100 experiments with each algorithm of the ED

Table 6: Results obtained by System 1 (6 unit system).

	Min. Cost	Mean. Cost	Std. Cost	Max. Cost
Hopfield NN	15485.9374	15485.9374	0	15485.9374
		$M = 100, G_{max} = 200$		
GA	15445.5961	15465.1757	9.7336	15491.4797
DE	15444.9466	15450.1339	6.9854	15472.0651
ACSA	15445.3052	15459.5170	12.0247	15511.5269
BCO	15444.5837	15459.9441	8.4816	15482.3963
AIS	15446.3283	15456.6660	7.3954	15481.2766
FA	15445.9448	15461.3003	9.3385	15501.3958
PSO	15444.7756	15466.5658	7.9185	15483.9700
SPSO	15443.0188	15452.4764	9.5316	15490.2621
CPSO	15442.9892	15449.1213	5.8048	15466.3953
APSO	15445.5109	15473.3164	12.9048	15538.6016
HGPSO	15447.1055	15462.6151	10.6456	15497.0335
HPSOM	15443.6281	15449.2603	6.2745	15479.8640
QPSO	15442.9803	15455.6220	11.6388	15482.2709
G-QPSO	15443.2303	15473.3521	42.1254	15493.2412
SG-QPSO	15442.7831	15445.0319	3.2756	15455.3582
		$M = 20, G_{max} = 1000$		
GA	15446.4787	15465.9948	10.7090	15493.2033
DE	15442.9836	15455.2537	13.7447	15489.8981
ACSA	15445.3052	15462.5170	12.0247	15511.5269
BCO	15446.3788	15461.8471	11.6661	15503.2901
AIS	15443.1652	15458.0859	8.5894	15481.0627
FA	15447.1955	15466.3277	12.5520	15512.0039
PSO	15443.8360	15459.9688	13.3737	15529.6094
SPSO	15442.9130	15477.9615	33.7155	15597.4534
CPSO	15443.1280	15454.1791	8.0500	15460.4890
APSO	15444.8934	15459.4084	11.0307	15493.3795
HGPSO	15445.4041	15464.3992	11.5621	15494.0358
HPSOM	15443.1716	15464.8451	22.8483	15533.1786
QPSO	15443.0583	15465.4058	25.8660	15518.4093
G-QPSO	15443.5143	15469.2825	56. 4224	1503.1225
SG-QPSO	15442.8105	15453.9682	13.1657	15482.7553

Table 7: $M = 100, G_{max} = 200$ SG-QPSO system 1 (6-unit system).

		Power output:P_1 (MW) ~ P_6 (MW)			
445.5381	172.8535	263.7547	141.3865	163.7148	89.1707
Total power output(MW)				1276.4183	
Power loss(MW)				12.4173	
Total generation cost($/h)				15442.7631	

The best solution is obtained with 100 runs.

problem on System 2. Obviously, in any experiment configurations, SG-QPSO obtained the lowest cost. It can be seen that when $M = 100$ and $G_{max} = 200$, QPSO ranks second with a mean cost of 15455.6220$/h. When $M = 20$ and $G_{max} = 1000$, the second-best method is HPSOM, and its average cost is 32811.3701$/h. In the two experimental settings, the worst-performing optimization algorithms are BCO (mean cost 33113. 0149$/h) and GA (mean cost 33188.5443$/h).

Table 9 lists the results of the ED problem of each algorithm on System 3. From this table, in all the algorithms of the two experiment configurations, SG-QPSO achieved the best results. When $M = 100, G_{max} = 200$, the second-best performing algorithm is HPSOM, and the average cost obtained in 100 experiments is 131614.7211 $/h. In this set of experiments, GA performed the worst among all the algorithms participating in the test.

In two different experiments configurations, the best solution to the system is obtained through the SG-QPSO algorithm. The minimum cost of the algorithm in 100 runs was 32663.2635 $/h. Table 10 shows the corresponding total power generation cost for the best solution is 32663.2635 $/h when $M = 20$ and $G_{max} = 1000$. From Table 9, the difference between the available load (2659.5748 MW–29.5683 MW) and the load demand (2630 MW) is 0.0065, which proves that the power balance equation constraint in (9) and (18) is satisfied. Figure 2 shows that for this ED problem, the SG-QPSO method has better convergence than other

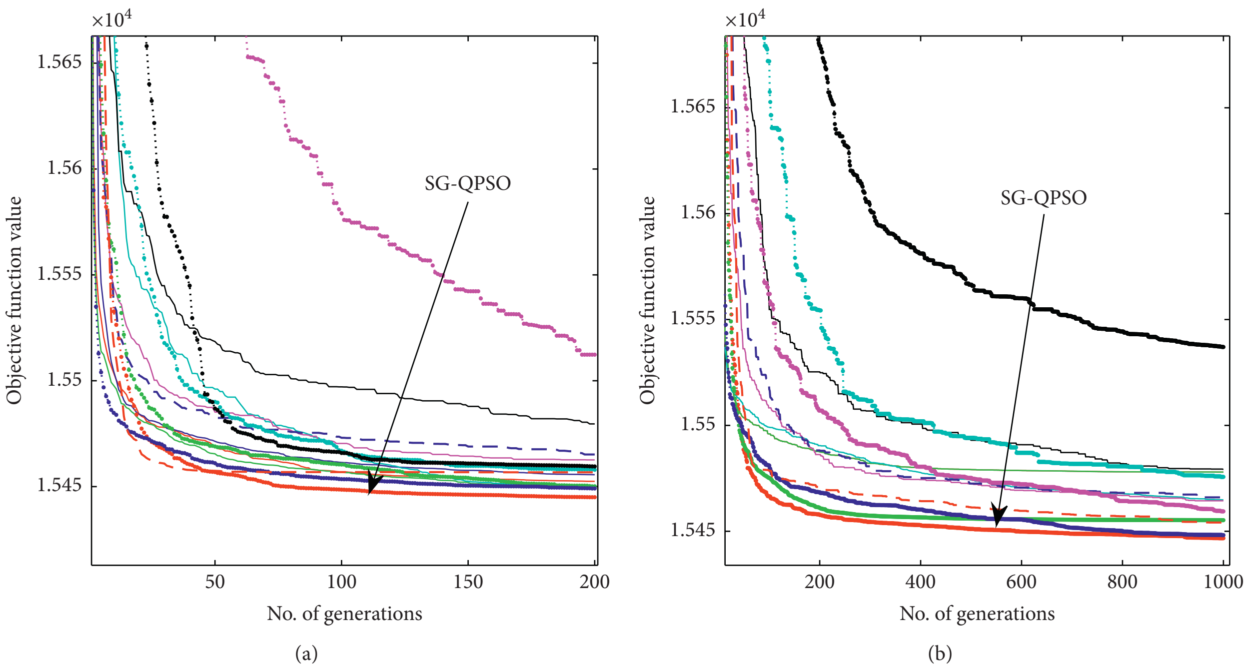

Figure 1: Convergence properties of the tested optimization methods for the 6-unit system with (a) $M = 100$ and $G_{\max} = 200$; (b) $M = 20$ and $G_{\max} = 1000$.

Table 8: Results obtained by System 2 (15 unit system).

	Min. cost	Mean. cost	Std. cost	Max. cost
Hopfield NN	34281.4857	34281.4857	0	34281.4857
		$M = 100, G_{\max} = 200$		
GA	32939.5208	33106.0019	100.1279	33231.6216
DE	32818.5792	32990.8673	61.5145	33116.9340
ACSA	32785.6031	33051.7711	77.8005	33185.2761
BCO	32989.2341	33113.0149	69.7986	33301.4940
AIS	32895.9173	33017.6537	58.1230	33132.0191
FA	32901.6610	33081.0107	91.0111	33197.2718
PSO	32715.0957	32940.4603	121.8668	33450.0099
SPSO	32675.3597	32840.9538	93.5420	33049.5619
CPSO	32705.5390	32917.4052	111.2425	33138.0568
APSO	32687.9840	32948.0533	92.0044	33359.6609
HGPSO	32864.0501	33034.1894	63.9932	33280.2655
HPSOM	32697.2458	32819.5931	83.0907	33015.7284
QPSO	32689.3055	32802.9367	75.6095	33045.0659
G-QPSO	32702.2125	32853.1352	79.1024	33132.1642
SG-QPSO	32671.2583	32745.5195	57.6386	32947.5837
		$M = 20, G_{\max} = 1000$		
GA	32905.3592	33188.5443	88.9124	33273.1660
DE	32718.8201	32966.4332	110.32378	33213.3173
ACSA	32863.1770	33120.0202	86.6134	33256.2899
BCO	32789.2342	33030.8636	69.7986	33301.4940
AIS	32895.9173	33017.6537	58.1230	33132.0191
FA	32898.0118	33116.9006	96.3875	33310.7299
PSO	32735.6944	33039.0837	102.0513	33297.2240
SPSO	32697.1431	32933.5688	137.8462	33399.6968
CPSO	32774.8653	32897.7110	112.1387	33372.1291
APSO	32861.4413	32996.4562	84.8760	33255.0095
HGPSO	32782.2876	33019.8081	139.8065	33413.7438
HPSOM	32677.3925	32811.3701	74.8198	32992.3424
QPSO	32675.4806	32794.6370	98.5369	33106.1779
G-QPSO	36932.1185	32833.3232	183.1024	33132.4262
SG-QPSO	32663.2635	32758.6330	84.1633	32973.1083

Table 9: Results obtained by System 3 (40-unit system).

	Min. Cost	Mean. Cost	Std. Cost	Max. Cost
Hopfield NN	136443.7361	136443.7361	0	136443.7361
		$M = 100, G_{\max} = 200$		
GA	133032.8559	135162.1174	766.2829	137015.1418
DE	130560.8784	131763.7215	672.3205	133321.1490
ACSA	130888.1295	133885.6102	981.6510	135768.9684
BCO	131611.6984	132963.8364	601.3297	134148.5434
AIS	130659.0464	132615.3328	629.3222	133885.6066
FA	131689.6980	133752.5505	778.3255	135385.4171
PSO	131782.8393	132854.3789	685.4071	134768.2045
SPSO	130015.4388	131732.2893	963.8586	134795.8482
CPSO	130076.3782	131893.6162	869.5377	133774.6663
APSO	131095.8262	132350.7739	581.2420	133824.5656
HGPSO	131673.7544	133013.4195	671.3449	135075.4546
HPSOM	130513.9921	131614.7211	591.2488	133070.5908
QPSO	130415.6348	131458.0662	578.0477	132863.7305
GQPSO	131323.2141	131721.2426	621.2423	133002.2331
SG-QPSO	130383.7947	131269.5009	490.5704	132458.4669
		$M = 20, G_{\max} = 1000$		
GA	133435.6906	135012.4985	729.3536	136274.9726
DE	129915.5635	130600.2269	1335.4343	137042.9461
ACSA	131167.3417	132844.7110	741.0843	13492.36245
BCO	130337.7290	131733.9439	589.8034	132999.8803
AIS	130133.9214	131482.2767	561.7950	132703.1884
FA	130948.8466	133511.4572	747.3692	134997.9243
PSO	130887.0844	132614.1979	618.8210	135008.7394
SPSO	129616.8801	130455.3715	1379.2113	138444.9147
CPSO	129638.4548	130812.0434	651.0647	134184.2693
APSO	130861.5242	132587.8486	675.0306	134044.6303
HGPSO	132072.2495	134012.5706	684.4951	135528.3862
HPSOM	129177.4413	130234.1694	529.5827	131281.3077
QPSO	129519.5044	130498.1964	573.5890	132264.9375
GQPSO	131213.3145	131417.2211	598.2213	133102.1132
SG-QPSO	129078.4705	129884.6948	549.4955	131198.4069

Table 10: $M = 20, G_{max} = 1000$ SG-QPSO system 2 (15-unit system).

	Power Output			
$P_1 \sim P_4$ (MW)	455.1085	380.9460	126.6947	127.8492
$P_5 \sim P_8$ (MW)	170.7069	463.8439	427.6885	75.3608
$P_9 \sim P_{12}$ (MW)	50.7581	163.3610	77.6944	80.5684
$P_{13} \sim P_{15}$ (MW)	25.7335	20.5853	12.6756	
Total power output(MW)		2659.5748	Power loss(MW)	29.5683
Total generation cost($/h)			32663.2635	

The best solution is obtained with 100 runs.

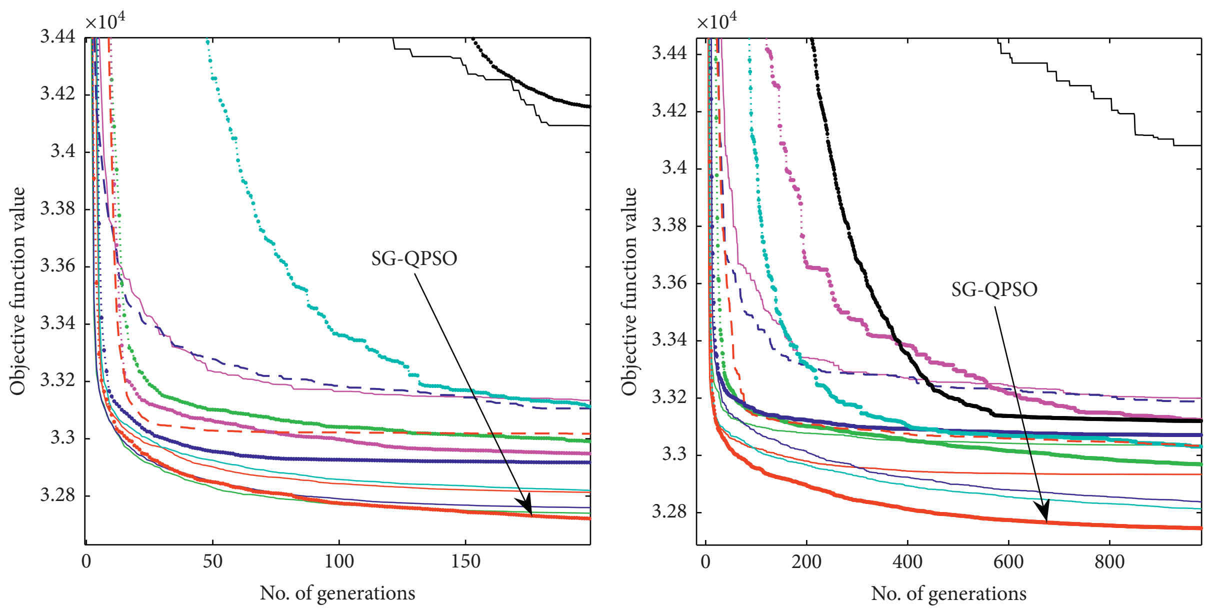

Figure 2: Convergence properties of the tested optimization methods for the 15-unit system with (a) $M = 100, G_{max} = 200$; (b) $M = 20, G_{max} = 1000$.

Table 11: The best solution obtained by using SG-QPSO for System 3 (40-unit system).

Total Power Output(MW)	8631.9425
Power loss(MW)	81.9390
Total generation cost($/h)	129078.4705

Use $M = 20, G_{max} = 1000$ (100 runs).

algorithms, providing faster convergence speed and the best final mean fitness value.

From Table 9, when $M = 20, G_{max} = 1000$, the SG-QPSO algorithm can obtain the best solution to the ED problem of the system. Due to the space limitations of this article, we only list the best results of total power output and system transmission loss obtained when the minimum total cost is 129078.4705 $/h in Table 11. In order to prove that the equality constraints in (9) and (18) are satisfied, we will combine the left side of (9) (that is, total output power (8631.9425 MW)) and the right side of (9) (that is, power loss (81.9390 MW)) and the sum of the load demand (8550 MW) (8631.9425 MW) is compared, and both satisfy the equality constraints. In addition, as shown in Figure 3, SG-QPSO also has the best convergence for the fitness value of the ED problem of the system.

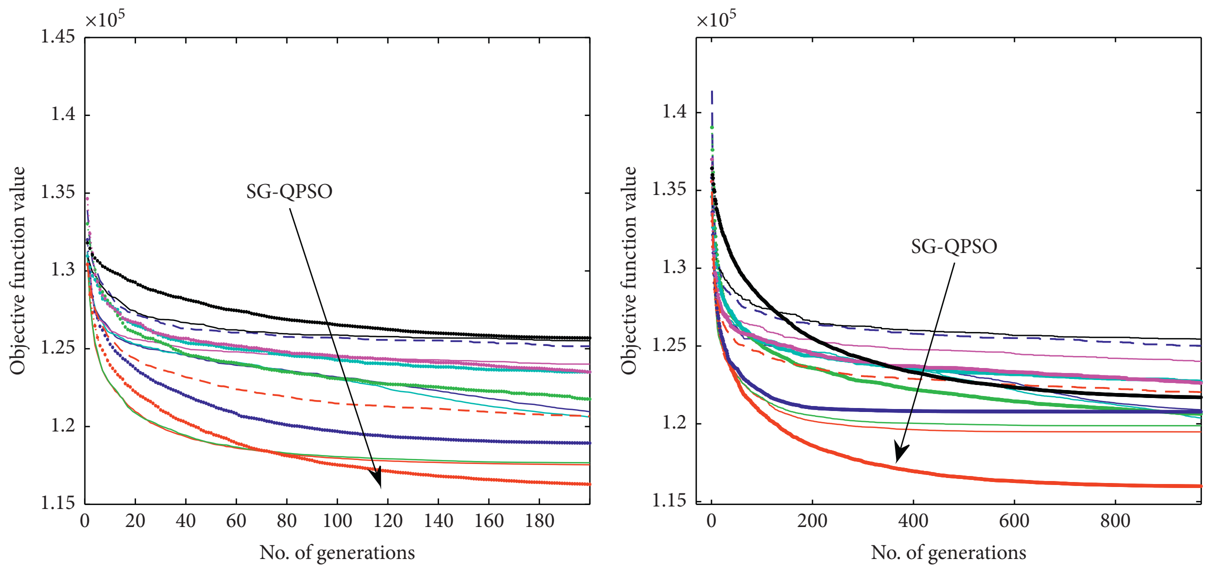

Figure 3: Convergence properties of the tested optimization methods for the 40-unit system with (a) $M = 100, G_{\max} = 200$; (b) $M = 20, G_{\max} = 1000$.

5. Conclusion

A shrink Gaussian distribution Quantum-behaved particle swarm optimization (SG-QPSO) algorithm is proposed to effectively solve the power economic dispatch problem by considering the nonlinear characteristics of the generator. SG-QPSO yields better solutions of different systems compared to any other tested algorithms, and highly similar optimization results among 100 independent trails of each system confirmed its robustness. In addition, the performance of SG-QPSO shows a stronger global search performance, which can be seen from the relatively low system cost obtained in 100 runs. Therefore, the SG-QPSO method is a promising tool for solving ED problems and other optimization problems in the industrial field. Our future work will focus on the application of the SG-QPSO method on other industrial problems, as well as the theoretical analysis of the algorithm search mechanism.

Data Availability

The experimental data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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