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Quantum-behaved Electromagnetism-like Mechanism Algorithm for Economic Load Dispatch of Power System

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Abstract – This paper presents a new algorithm called Quantum-behaved Electromagnetism-like Mechanism Algorithm which is used to solve economic load dispatch of power system. Electromagnetism-like mechanism algorithm simulates attraction and repulsion mechanism for particles in the electromagnetic field. Every solution is a charged particle, and it move to optimum solution according to certain criteria. Quantum-behaved electromagnetism-like mechanism algorithm merges quantum computing theory with electromagnetism-like mechanism algorithm. Superposition characteristic of quantum methodology can make a single particle present several states, and the characteristic potentially increases population diversity. Probability representation of quantum methodology is to make particle state be presented according to a certain probability. And the quantum rotation gates are used to realize update operation of particles. The algorithm is tested for 13-generator system and 40-generator system, which validates it can effectively solve economic load dispatch problem. Through performance comparison, it is obvious the solution is superior to other optimization algorithm.

Keywords: Economic load dispatch, Power system, Quantum-behaved electromagnetism-like mechanism algorithm, Value-point effects

1. Introduction

Economic load dispatch (ELD) is one of the major mathematical optimization issues in power system operation. It seeks "the best" generation schedule for the generating plants to supply the required demand with the minimum production cost. The input-output characteristics of modern generators are nonlinear by nature. To solve ELD problem, a lot of conventional methods such as the lambda iteration method, the gradient method, Newton's method etc. have been employed. Unfortunately, for generating units with nonlinear characteristics, the conventional methods can hardly achieve the optimal or near optimal solution. Recently more and more interests have been focused on the application of artificial intelligent technology for solution of ELD problems. Several artificial intelligence methods, such as genetic algorithms [1], evolutionary programming algorithm [2], clonal algorithm [3], neural network [4] etc. have been developed and applied successfully to ELD problems.

Electromagnetism-like mechanism algorithm originates from the electromagnetism theory of physics [5], which considering potential solutions as electrically charged particles spread around the solution space. It has been effectively used in different sorts of research and engineering problems, such as neural network training [6], vehicle routing problems [7] flow shop scheduling problems [8], communication [9], array pattern optimization in circuits [10], image processing [11], intelligent forecasting [12], and control systems [13] and so on. But EMA exist some defects such as premature convergence etc.

Quantum-behaved electromagnetism-like mechanism Algorithm (QEMA) is proposed and used to solve ELD problem. QEMA merges quantum computing theory with electromagnetism-like mechanism algorithm. The super-position characteristic and probability representation of quantum methodology are combined into electromagnetism-like mechanism Algorithm. This can make a single particle be expressed by several certain probability states. And the quantum rotation gates are used to realize update operation of particles. The algorithm is tested for 13-generator system and 40-generator system, which validates it can effectively solve ELD problem.

2 ELD Problem Formulation

2.1 Objective function considering valve-point loading effects

The main objective is to minimize the fuel cost while satisfying the load demand with operating constraints. The objective function can be described as an minimization process with the objective:

$$F = \sum_{i=1}^{s} f_i(P_i) \tag{1}$$

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where F is the cost function; s is the number of generators in the system; P_i is the power of generator i (in MW); $f_i(P_i)$ is the total fuel cost for the ith generator(in \$/h).

Cost functions comprise very different input-output curves, since each generator has multi-valve steam turbines. A sinusoidal function is incorporated into a quadratic function to consider the value-point loadings. Cost functions addressing the valve-point loadings of generating units are given by

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| g_i \sin(h_i(P_i - P_i^{\min})) \right| \quad (2)$$

where a_i, b_i, c_i are the fuel cost coefficients of the ith unit; g_i and h_i are the coefficients of generator i reflecting the valve point effects; $P_i^{\min}$ is the output of the minimum operation of the generating unit i (in MW).

2.2 Constraint conditions

The above objective function is to be minimized subject to the following constraints.

2.2.1 Thermal power limits constraint

Thermal units can generate power between specified maximum and minimum limits. These inequality constraints are expressed as

$$P_i^{\min} \le P_i \le P_i^{\max} \quad i = 1, 2, \cdots, s \quad (3)$$

where $P_i^{\max}$ is the output of the maximum operation of the generating unit i (in MW).

2.2.2 System active load balance constraint

Total generated power is equal to the total demand in the dispatch interval, as shown in (4).

$$\sum_{i=1}^{s} P_i = P_L \quad (4)$$

where P_L is the system load demand (in MW).

3. Quantum-behaved Electromagnetism-like Mechanism Algorithm

3.1 Basic electromagnetism-like mechanism algorithm

EMA imitates the attraction-repulsion mechanism between charged particles in an electromagnetic field. In EMA methodology, every particle represents a solution and carries a certain amount of charge which is proportional to the solution quality. Solutions are in turn defined by position vectors which give the real positions of particles in a multi-dimensional space. Moreover, objective function values of particles are calculated based on these position vectors. Each particle exerts repulsion or attraction forces on other population members and a resultant force on a particle is used to update its position. The idea behind the EMA methodology is to move particles towards the optimum solution by exerting attraction or repulsion forces.

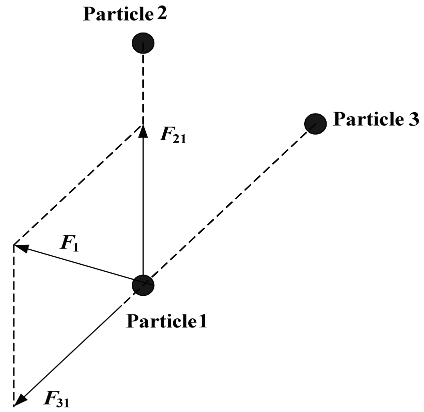

Fig. 1. Schematic diagram of attraction and repulsion mechanism for particles

There are three particles in schematic diagram of attraction and repulsion mechanism for particles (see Fig. 1). If particle 2 is better than particle 1, while particle 3 is worse than particle 1, the attraction force exerted on particle 1 by particle 2 is F_{21}, and the repulsion force exerted on particle 1 by particle 3 is F_{31}. F_1 is the total force exerted on particle 1 by particle 2 and particle 3. Particle 1 will move along with the total force F_1, and it can move to better region.

3.2 Quantum-behaved electromagnetism-like mechanism algorithm

The concept of quantum computing was proposed in the early 1980s [14]. Many efforts on quantum computing have progressed actively because these computing shown to be more powerful that classical computing on various specialized problems [15, 16]. QEMA merges quantum computing theory with EMA. Superposition characteristic of quantum methodology can make a single particle present several states, and the characteristic potentially increases population diversity. Probability representation of quantum methodology is to make particle state be presented according to a certain probability. And the quantum rotation gates are used to realize update operation of particles.

3.2.1 Qubit

A particle is denoted by Qubit for QEMA. A Qubit may be in the “1” state, in the “0” state, or in any superposition of the two, while a bit in EMA can only hold a single state, either 0 or 1. The state of a Qubit can be represented as

$$|\psi\rangle = \alpha |0\rangle + \beta |1\rangle \quad (5)$$

where α and β are complex numbers, satisfying

$$|\alpha|^2 + |\beta|^2 = 1 \tag{6}$$

$|0>$ represents the state of spin up, while $|1>$ represents the state of spin down, so a Qubit can represent two state information ($|0>$ and $|1>$) simultaneously. The superposition state can also expressed in (7).

$$|\psi>= \cos\theta\,|0> + \sin\theta\,|1> \tag{7}$$

where θ is phase of Qubit, the relation among θ and α and β, satisfying

$$\theta = \arctan\frac{\beta}{\alpha} \tag{8}$$

Then m particles can be expressed by (9) or (10).

$$\begin{bmatrix} \alpha_1 \big| \alpha_2 \big| \alpha_3 \big| \cdots \big| \alpha_m \\ \beta_1 \big| \beta_2 \big| \beta_3 \big| \cdots \big| \beta_m \end{bmatrix} \tag{9}$$

$$[\theta_1 \,|\, \theta_2 \,|\, \theta_3 \,|\cdots|\, \theta_m] \tag{10}$$

3.2.2 Steps of QEMA

The steps of QEMA is described as Fig. 2.

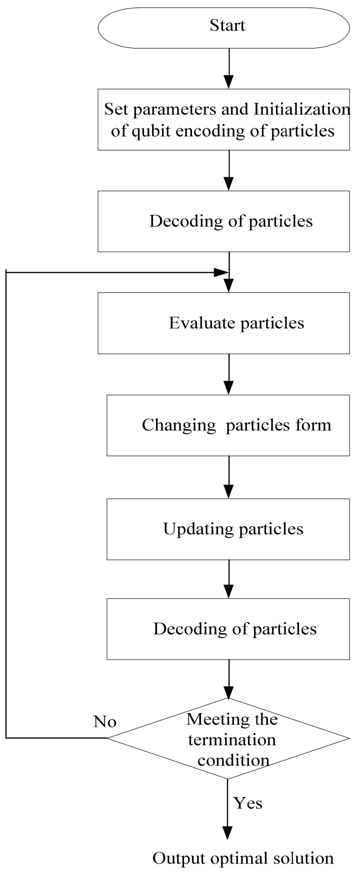

Fig. 2. The Flowchart of QEMA

Some core steps of QEMA can be introduced in following parts.

3.2.3 Initialization of Qubit encoding of particles

There are m particles ($X_1, X_2, \cdots, X_i, \cdots, X_m$) in n-dimensional search space. The *ith* particle can be recorded as $X_i = (\theta_{i,1}, \theta_{i,2}, \cdots \theta_{i,j}, \cdots, \theta_{i,n})$. S is matrix composing with probability amplitude of particles. $s(1, j, i)$ expressed α_{ij} (α of jth dimension of ith particle). $s(2, j, i)$ denoted β_{ij} (β of jth dimension of ith particle). The initialization process can be described in (11) and (12).

$$s(1, j, i) = r \tag{11}$$

$$s(2, j, i) = \sqrt{1-r^2} \tag{12}$$

where r is random number from 0 to 1.

According to above description, the relation among $\theta_{i,j}$, α_{ij} and β_{ij} can be described in (13).

$$\theta_{i,j} = \arctan\frac{\beta_{ij}}{\alpha_{ij}} \tag{13}$$

3.2.4 Decoding of particles

When a particle collapses into a basic state, the probability of occurrence of the basic state need be expressed to participate in the fitness assessment of particles. Supposed the actual parameter space searched by algorithm is [a, b], and the occurred probability of some state is [0, 1], then the probability need to be decoded into the actual parameter space [a, b]. The decoding process can be expressed by (14).

$$\begin{cases} c(i, j) = s(2, j, i)^2 * (b-a) + a & r < p \\ c(i, j) = s(1, j, i)^2 * (b-a) + a & r \geq p \end{cases} \tag{14}$$

Where p is the choice probability of state expression; r is random number from 0 to 1; $s(1, j, i)$ expressed α of jth dimension of ith particle. $s(2, j, i)$ denoted β of jth dimension of ith particle. $c(i, j)$ denotes actual parameter values of jth dimension of ith particle.

3.2.5 Evaluating particles

Evaluating particles is based on the minimum of the total fuel cost. (Seeing section 2.1)

3.2.6 Changing particles form

In the course of changing particles form, the probability amplitude expression transforms into phase expression according to (8).

3.2.7 Updating particles

The first step of updating particles is to calculating the phase correction, which includes calculation of force and movement of particles.

(1) Calculation of force

QEMA is via calculating the resultant force in the population to determine moving direction of the current particle by Coulomb's law and superposition principle. The resultant force is inversely proportional to the distance between the particles and directly proportional to their charges.

The first step in the force calculation is the calculation of the charge for each particle. The charge of particle can decide the size of own attraction or repulsion force, and can affect the size of attraction or repulsion force of other particles.

The charge of the *ith* particle $X_i = (\theta_{i,1}, \theta_{i,2}, \cdots \theta_{i,j}, \cdots, \theta_{i,n})$ is shown as follows:

$$q_i = \exp\left(-n \frac{f(X_i) - f(X_{best})}{\sum_{k=1}^{m} (f(X_k) - f(X_{best}))} \right) \tag{15}$$

where q_i is the charge for the *ith* particle; m is the population size; n is the dimension number of particle; $f(X_i)$, $f(X_k)$ and $f(X_{best})$ denote the objective value of the *ith* particle, the *kth* particle and the best solution.

After the charge is calculated, the resultant force of the *ith* particle can be calculated as

$$F_i = \sum_{j \neq i}^{m} \begin{cases} (X_j - X_i)\dfrac{q_i q_j}{\left\| X_j - X_i \right\|^2} & if\ f(X_j) < f(X_i) \\ (X_i - X_j)\dfrac{q_i q_j}{\left\| X_j - X_i \right\|^2} & if\ f(X_j) > f(X_i) \end{cases} \tag{16}$$

where $f(X_j) < f(X_i)$ represents attraction and $f(X_j) < f(X_i)$ represents repulsion. As can be seen from Eq.(17) above, F_i is directly proportional to the the charge values of the particles and is inversely proportion to the distance between the *ith* particle and the *jth* particle. Because the objective value of the particle X_{best} is best, it is an absolute attraction particle, and it can attract other particles.

(2) Movement of particles

Each particle moves according to the resultant force which can be given as

$$\Delta X_i = \lambda \frac{F_i}{\left\| F_i \right\|} V \tag{17}$$

where $\Delta X_i = (\Delta\theta_{i,1},\ \Delta\theta_{i,2}, \cdots \Delta\theta_{i,j}, \cdots,\ \Delta\theta_{i,n})$. λ is a random step length, which is uniformly distributed between 0 and 1. V denotes the allowed range of movement toward the lower or upper bound for the corresponding dimension.

Next step is calculating quantum rotation gate to update particles.

$$\begin{bmatrix} \alpha_{ij}^{t+1} \\ \beta_{ij}^{t+1} \end{bmatrix} = \begin{bmatrix} \cos\Delta\theta_{i,j}^{t+1} & -\sin\Delta\theta_{i,j}^{t+1} \\ \sin\Delta\theta_{i,j}^{t+1} & \cos\Delta\theta_{i,j}^{t+1} \end{bmatrix} \begin{bmatrix} \alpha_{ij}^{t} \\ \beta_{ij}^{t} \end{bmatrix} \tag{18}$$

where $\Delta\theta_{i,j}^{t+1}$ denotes phase correction of *j*th dimension of *i*th particle in the t+1th iterative course; α_{ij}^{t} , β_{ij}^{t} are probability amplitudes of *j*th dimension of *i*th particle in the *t*th iterative course; α_{ij}^{t+1} , β_{ij}^{t+1} are probability amplitudes of *j*th dimension of *i*th particle in the *t*+1th iterative course.

4. Simulation Results

The applicability and validity of QEMA for practical applications has been tested on two test cases.

- **Test Case 1**

A system with 13 generators with value-point loading is used here to check the feasibility of QEMA. The unit characteristics like cost coefficients along with value-point loading coefficient, operating limits of generators are given in Table 1. The data shown in Table 1 are also available in [17]. The total load is 1800MW.

The following QEMA parameters have been used after a number of careful experimentation: Number of particles m =100; Dimension number of particles n =13.

Simulation results can be described in Table 2.

In order to verify the performance advantages of QEMA further, the simulation results were compared with that of other optimized algorithm, and the comparison results in Table 3. Algorithm 1 is QEMA which have been applied in this paper; Algorithm 2~Algorithm 5 is evolutionary programming algorithm which have been proposed in [18]; Algorithm 6 is improved genetic algorithm which have

Table 1. Units data for test case 1

Unit	a_i	b_i	c_i	g_i	h_i	P_{min}	P_{max}
1	0.00028	8.10	550	300	0.035	0	680
2	0.00056	8.10	309	200	0.042	0	360
3	0.00056	8.10	307	200	0.042	0	360
4	0.00324	7.74	240	150	0.063	60	180
5	0.00324	7.74	240	150	0.063	60	180
6	0.00324	7.74	240	150	0.063	60	180
7	0.00324	7.74	240	150	0.063	60	180
8	0.00324	7.74	240	150	0.063	60	180
9	0.00324	7.74	240	150	0.063	60	180
10	0.00284	8.60	126	100	0.084	40	120
11	0.00284	8.60	126	100	0.084	40	120
12	0.00284	8.60	126	100	0.084	55	120
13	0.00284	8.60	126	100	0.084	55	120

Table 2. Simulation results of case 1 for QEMA

Unit	Solution	Unit	Solution
P_1/MW	628.23	P_8/MW	109.64
P_2/MW	149.40	P_9/MW	60.00
P_3/MW	224.18	P_{10}/MW	40.00
P_4/MW	109.63	P_{11}/MW	40.00
P_5/MW	109.61	P_{12}/MW	55.00
P_6/MW	109.61	P_{13}/MW	55.00
P_7/MW	109.66	*cost*/$	17965

Table 3. The performance comparison of case 1 for some optimization algorithm

Algorithm	1	2	3	4
cost/$	17965	18048	18018	18028
Algorithm	5	6	7	
cost/$	17994	18063	18013	

Table 4. Units data for test case 2

Unit	a_i	b_i	c_i	g_i	h_i	P_{min}	P_{max}
1	0.00690	6.73	94.705	100	0.084	36	114
2	0.00690	6.73	94.705	100	0.084	36	114
3	0.02028	7.07	309.54	100	0.084	60	120
4	0.00942	8.18	369.03	150	0.063	80	190
5	0.0114	5.35	148.89	120	0.077	47	97
6	0.01142	8.05	222.33	100	0.084	68	140
7	0.00357	8.03	287.71	200	0.042	110	300
8	0.00492	6.99	391.98	200	0.042	135	300
9	0.00573	6.60	455.76	200	0.042	135	300
10	0.00605	12.9	722.82	200	0.042	130	300
11	0.00515	12.9	635.20	200	0.042	94	375
12	0.00569	12.8	654.69	200	0.042	94	375
13	0.00421	12.5	913.40	300	0.035	125	500
14	0.00752	8.84	1760.4	300	0.035	125	500
15	0.00708	9.15	1728.3	300	0.035	125	500
16	0.00708	9.15	1728.3	300	0.035	125	500
17	0.00313	7.97	647.85	300	0.035	220	500
18	0.00313	7.95	649.69	300	0.035	220	500
19	0.00313	7.97	647.83	300	0.035	242	550
20	0.00313	7.97	647.81	300	0.035	242	550
21	0.00298	6.63	785.96	300	0.035	254	550
22	0.00298	6.63	785.96	300	0.035	254	550
23	0.00284	6.66	794.53	300	0.035	254	550
24	0.00284	6.66	794.53	300	0.035	254	550
25	0.00277	7.10	801.32	300	0.035	254	550
26	0.00277	7.10	801.32	300	0.035	254	550
27	0.52124	3.33	1055.1	120	0.077	10	150
28	0.52124	3.33	1055.1	120	0.077	10	150
29	0.52124	3.33	1055.1	120	0.077	10	150
30	0.01140	5.35	148.89	120	0.077	47	97
31	0.00160	6.43	222.92	150	0.063	60	190
32	0.00160	6.43	222.92	150	0.063	60	190
33	0.00160	6.43	222.92	150	0.063	60	190
34	0.0001	8.95	107.87	200	0.042	90	200
35	0.0001	8.62	116.58	200	0.042	90	200
36	0.0001	8.62	116.58	200	0.042	90	200
37	0.0161	5.88	307.45	80	0.098	25	110
38	0.0161	5.88	307.45	80	0.098	25	110
39	0.0161	5.88	307.45	80	0.098	25	110
40	0.00313	7.97	647.83	300	0.035	242	550

been proposed in [19]. Algorithm 7 is EMA.

It can be seen from Table 3 that QEMA is superior to EMA, other evolutionary programming algorithms and improved genetic algorithm.

Table 5. Simulation results of case 2 for QEMA

Unit	Solution	Unit	Solution
P_1/MW	111.18	P_{21}/MW	523.98
P_2/MW	110.96	P_{22}/MW	523.29
P_3/MW	97.94	P_{23}/MW	523.41
P_4/MW	179.81	P_{24}/MW	522.89
P_5/MW	92.62	P_{25}/MW	523.96
P_6/MW	139.49	P_{26}/MW	522.36
P_7/MW	259.91	P_{27}/MW	10.83
P_8/MW	284.92	P_{28}/MW	10.82
P_9/MW	284.44	P_{29}/MW	10.00
P_{10}/MW	130.68	P_{30}/MW	87.79
P_{11}/MW	168.84	P_{31}/MW	189.85
P_{12}/MW	167.01	P_{32}/MW	189.71
P_{13}/MW	213.45	P_{33}/MW	189.99
P_{14}/MW	303.90	P_{34}/MW	163.50
P_{15}/MW	394.92	P_{35}/MW	164.84
P_{16}/MW	394.95	P_{36}/MW	164.82
P_{17}/MW	489.06	P_{37}/MW	109.99
P_{18}/MW	489.70	P_{38}/MW	110.00
P_{19}/MW	511.84	P_{39}/MW	109.98
P_{20}/MW	511.52	P_{40}/MW	511.25
cost/$		121570	

Table 6. The performance comparison of case 2 for some optimization algorithm

Algorithm	1	2	3	4	5
cost/$	121570	123488	122679	122647	122624
Algorithm	6	7	8	9	10
cost/$	122252	122122	122000	121819	122430

- **Test Case 2**

This case study consisted of 40 thermal units of generation with the effects of valve-point loading, as given in Table 2. The data shown in Table 4 are also available in [13]. In this case, the total load is 10500MW.

The following QEMA parameters have been used after a number of careful experimentation: Number of particles m =300; Dimension number of particles n =40.

Simulation results can be described in Table 5.

In order to verify the performance advantages of QEMA further, the simulation results were compared with that of other optimized algorithm, and the comparison results in Table 6. Algorithm 1 is QEMA which have been applied in this paper; Algorithm 2 ~ Algorithm 5 are evolutionary programming algorithm which have been proposed in [13]; Algorithm 6 ~ Algorithm 9 are MPSO algorithm, ESO algorithm, GA-MU algorithm and IGAMU algorithm which have been presented in [1]. Algorithm 10 is EMA.

It can be seen from Table 6 that QEMA is superior to EMA and other algorithms. It can solve ELD problem effectively.

5. Conclusion

This paper presents a new algorithm called QEMA which is used to solve economic load dispatch of power system. QEMA merges quantum computing theory with electromagnetism-like mechanism algorithm. Superposition characteristic of quantum methodology can make a single particle present several states, and the characteristic potentially increases population diversity. Probability representation of quantum methodology is to make particle state be presented according to a certain probability. And the quantum rotation gates are used to realize update operation of particles. Through performance comparison, it is obvious the solution is superior to EMA and other optimization algorithm. QEMA can effectively solve ELD problem in power systems.

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