A Chaos Quantum Immune Algorithm for Generation Expansion Planning

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Abstract. By integrating the ergodicity of chaos searching and the high efficiency of quantum computation into immune optimization, a novel chaos quantum immune algorithm for Generation Expansion Planning computation is presented. In this algorithm, antibodies in colonies are coded by quantum bits and updated by quantum rotation gates. To change phase of qubit, two different chaos variables are introduced into the quantum rotation gate. The one with the relatively small amplitude performs the cloning of excellent individuals to implement the local searching, and the other one with the relatively large amplitude performs the mutation of inferior individuals to realize the global searching. The convergence of the proposed algorithm has been proved. The experimental results indicate that the algorithm remarkably improves the convergence performance and the search efficiency of the immune optimization algorithm.

Introduction

Generation expansion planning is the most important decision-making activity in power system. The core problem to be solved by it is when, where and what kind of power plants should be built so as to meet the needs of power load development, that is, to seek for a generation expansion planning solution which can content the need of power load increase and various restrictive conditions with the minimal cost of national economic expenditure.

Due to the characteristics of generation expansion planning problems such as nonlinearity, discreteness, massive scale of power system, and existence of hundreds or more of medium-and long-term alternative generation expansion planning programs, there lie various troubles in sought of solutions for application normalization, e.g. difficulty in obtaining a global optimal solution, curse of dimensionality, issues with objective functions and constraint conditions, etc [1].

Artificial immune algorithm, as a simulating biological immune system of evolutionary algorithm, is a multi-point stochastic search algorithm. Compared with traditional analytical methods, the algorithm is better in global searches. In recent years, because of its great information processing capacity, especially its capability of complex calculations in parallel over all with distributed conditions, immune algorithm has been more frequently applied in nonlinear mixed optimization problems, and has been widely used in fields like reactive optimization of power system, distribution network switch optimization model, and calculation of optimal power flow, etc [2].

In this paper, an improved artificial immune algorithm is applied in generation expansion planning. According to simulation results, with application in generation expansion planning, immune algorithm can effectively avoid the dilemma of local optimal solution, improve local search ability, and speed up convergence rate.

Mathematical Model of Generation Expansion Planning

Generation expansion planning is aimed to seek for a generation expansion planning solution that can the need of power load increase and various restrictive conditions with the minimal cost of national economic expenditure within the entire planning period. With differences in service lifetime and initiation years, the remaining service life of various programs for generation expansion planning will be varied by the end of planning. For ease of comparison, uniform annual value method is used to calculate the equivalents of investment cost in terms of annual fees. Based on the characteristics of models, the objective function is defined as [1]:

$$OF_i = \sum_{t=0}^{T_i}(Z_{it} + O_{it} + Q_{it} - B_{it} - R_{it})(1+r)^{-t} + \sum_{t=0}^{T_j}(F_{g\bullet it} + F_{k\bullet it})(1+r)^{-(t+0.5)} + \sum_{j=1}^{M}\beta_j F_{ij} \text{ , } i = 1, 2, ..., N_f \qquad (1)$$

Wherein, Z_{it} represents the investment cost (RMB 10,000yuan) of Program i in the t th year; O_{it}, cost (RMB 10,000yuan) for losses of end power supply of Program i in the t th year, Q_{it}, cost (RMB 10,000yuan) for hydropower losses of waste water in hydropower plant for Program i in the t th year; B_{it}, hydroelectric and thermoelectric benefits (RMB 10,000yuan) other than power generation Program i in the t th year; R_{it}, recycling cost (RMB 10,000yuan) of residual value for Program i in the t th year; r, discount rate; T_i, number of planning years; N_f, program set with alternative plants; $F_{g\bullet it}$ and $F_{k\bullet it}$, respectively for fixed running maintenance cost and fuel cost for Program i in the t th year.

M represents constraint condition number; β_j, error costs for constraint condition j; F_{ij}, calculated value for the case that Program i can not meet the constraint condition.

Chaos quantum immune algorithm for Generation Expansion Planning

Immune evolutionary algorithm is a new optimization algorithm which refers to the information processing mechanism and principle of biological immune system. It has many excellent performances, such as antigen automatic identification, feature extraction, antibody diversification, distributed detection, learning and memory, self planning etc. So it is the parallel distributed adaptive system with enormous potential in the intelligent computation. Because it effectively use some useful information in solving problems, it can inhibit the "degenerate" phenomenon produced in the optimization process and jump out of the constraints of local minimum values. So that it can quickly limit the optimal solution in a smaller space range. But, the search efficiency conducted in a small space isn't satisfactory.

Chaos is a rather common phenomenon in nature. Although it seems confusing, it has a delicate interior structure with "random", "ergodicity" and " regularity " etc. features. And in a certain extent, it can traverse all states without repetition according to its own "law". The effects are significant when the chaos optimization method searches in a small space, while the effects are not ideal in a large space.

Quantum evolution algorithm is a recently developed probability search method, which combines quantum mechanism with evolutionary algorithm. Its essential character is to adopt the quantum bit coding chromosome and make full use of the superimposition and coherence of the quantum state. Compared with the traditional evolutionary algorithm, the quantum evolutionary computation has many advantages, such as the better population diversity and the ability of global optimization. Moreove, its performance of the algorithm is not affected when the population size is small.

Merging their respective spatial search advantages of the chaos optimization and the immune optimization as well as the efficiency of the quantum optimization, this paper puts forward a kind of chaos quantum immune algorithm. The algorithm adopts the quantum bits to initialize population and use the quantum rotation gate to update individuals. For the excellent individual's cloning amplification and the poor individual's mutations, it also respectively defines the scope of the quantum rotation's rotation angle. What's more, it introduces the chaos variable to traverse in the corresponding scope. The simulation results demonstrate that the algorithm has the advantages of fast convergence and great search ability while it keeps population diversity.

The steps to Generation Expansion Planning problem by chaos quantum immune algorithm:

Step 1. Fitness evaluation function

The chaotic quantum immune algorithm raised in this paper adopts formula(1) as the fitness evaluation function.

Step 2. Initial population

During the chaos optimization, the chaotic system used to produce chaotic variables adopts the logistic mapping: $x_{n+1} = \mu x_n(1-x_n)$

Use the following r Logistic mappings to produce r chaotic variables：

$$x_{n+1}^i = \mu_i x_n^i(1-x_n^i) \quad i=1,2,...,r \qquad (2)$$

In this formula, $\mu_i = 4$ and it is the chaotic attractor, i is the serial number of chaotic variables. Make n = 0, respectively give r chaotic variables' initial values, then get r chaotic variables from formula(2), i.e. $x_1^i(i=1,2,...,r)$. Employ the first antibody's qubit in the initialization population of r chaotic variables, make $n=1,2,...,N-1$, then create additional N-1 antibodies according to the above method. It is the N antibodies that makes up the initialization population.

Then, the No. n antibody is $P_n = \begin{vmatrix}\alpha_n^1 \\ \beta_n^1\end{vmatrix}\begin{vmatrix}\alpha_n^2 \\ \beta_n^2\end{vmatrix}\begin{vmatrix}\cdots \\ \cdots\end{vmatrix}\begin{vmatrix}\alpha_n^r \\ \beta_n^r\end{vmatrix}$ (3)

In this formula, $\alpha_n^i = \cos(2x_n^i\pi)$， $\beta_n^i = \sin(2x_n^i\pi)$.

Step 3. Solution space transformation

Every antibody in the population contains 2r quantum bits probability amplitudes. The 2r probability amplitudes can be mapped from unit space to solution space of optimization problem by employing linear transformation. Each probability amplitude in antibodies corresponds to a optimization variable in solution space. If the No.i qubit of P_n is $[\alpha_n^i, \beta_n^i]^T$, the corresponding variables in solution space are:

$$X_{1i}^n = \frac{1}{2}[b_i(1+\alpha_n^i) + a_i(1-\alpha_n^i)] \qquad (4)$$

$$X_{2i}^n = \frac{1}{2}[b_i(1+\beta_n^i) + a_i(1-\beta_n^i)] \qquad (5)$$

So, each antibody has two corresponding results in optimization problems, of which the probability amplitude α_n^i in the quantum state $|0\rangle$ corresponds to X_{1i}^n, the probability amplitude β_n^i in the quantum state $|1\rangle$ corresponds to X_{2i}^n, $i=1,2,\ldots,r$； $n=1,2,...,N$.

Step 4. Cloning and cloning amplification for individuals

Clone q (q < N) antibodies with the highest fitness selected from the population containing N antibodies, and use selected antibodies and new cloned antibodies to form a new new population. Suppose the selected q antibodies are $P_1, P_2, ..., P_q$, in descending order, according to the fitness. Then the antibodies' number is $N_k = \left[\frac{\rho N}{k}\right]$ through cloning the antibody $P_k(1 \le k \le q)$, in which $[\bullet]$ represents a rounding integer operation and ρ represents a given control parameter.

In order to maintain the population's size stability, when $\sum_{i=1}^q N_i < N-q$, formula (3) will create new antibodies' supplement; or take the first $N-q$ antibodies as a new population.

The cloning amplification is fulfilled through changing antibodies' qubits phase by the quantum rotation gate. Within traversal range of the quantum rotation gate's rotation angle, first give a cloning amplitude λ_k, then define the rotation gate according to $\Delta\theta_i^k = \lambda_k x_{n+1}^i$. For the traversal range shows the biphasic property, when the chaotic variables $x_{n+1}^i = 8x_n^i(1-x_n^i)-1$, the traversal range of $\Delta\theta_i^k$ is $[-\lambda_k, \lambda_k]$. In terms of the matrix needed amplification, the higher the fitness is, the smaller the superimposed chaos perturbation should be. So, make $\lambda_k = \lambda_0 \exp((k-q)/q)$, (λ_0 : control parameters), which will be used to control the size of chaos perturbation attached to the antibodies.

Supposing, the No. k cloning matrix is $P_k = \left|\begin{matrix}\cos(\theta_1^k) \\ \sin(\theta_1^k)\end{matrix}\right|\begin{matrix}\cos(\theta_2^k) \\ \sin(\theta_2^k)\end{matrix}\left|\begin{matrix}... \\ ...\end{matrix}\right|\begin{matrix}\cos(\theta_r^k) \\ \sin(\theta_r^k)\end{matrix}\right|$

The antibody, produced after the quantum rotation gate's cloning amplification, is $P_k = \left|\begin{matrix}\cos(\theta_1^k + \Delta\theta_{1s}^k) \\ \sin(\theta_1^k) + \Delta\theta_{1s}^k\end{matrix}\right|\begin{matrix}... \\ ...\end{matrix}\left|\begin{matrix}\cos(\theta_r^k + \Delta\theta_{rs}^k) \\ \sin(\theta_r^k + \Delta\theta_{rs}^k)\end{matrix}\right|$ $(s = 1, 2, \cdots, N_k)$

From the process of the above best antibodies' cloning amplification, we can see that the selected best antibodies have the role of optimizing coordinates, and in a small region the introduction of chaotic variables strengthens ergodicity of local optimization.

Step 5. Poorer antibodies' mutation operation

Transform the solution space to the population after cloning amplification, calculate each antibody's fitness, then carry out the chaos perturbation to antibodies' qubits phase by the quantum rotation gate, all of which can implement the mutation operation to m(m<N)antibodies' with lower fitness.

Firstly define a mutation amplitude $\breve{\lambda}_k$ which refers to the range of quantum rotation gate's rotation angle; secondly introduce the chaotic variables to determine the rotation angle size of quantum rotation gate. Then we can conclude that the lower the maternal fitness is, the greater the superimposed chaos perturbation is. For selected m antibodies with the lowest fitness, in the fitness ascending order, the No. k matrix's mutation amplitude $\breve{\lambda}_k = \breve{\lambda}_0 \exp((m-k)/m)$, in which λ_0 is control parameters to control the strength of antibodies' superimposed chaos perturbation. Usually make $\breve{\lambda}_0 = (5 \sim 10)\lambda_0$, now the range of the rotation angle is $[-\breve{\lambda}_k, \breve{\lambda}_k]$.

Step 6. Operation for new antibodies

Sort the population after cloning amplification and mutation according to the fitness, among which replace the d(d<N) antibodies of lower fitness with the new antibodies produced by formula(3). This process is equivalent to a chaotic search within the whole solution space, that is to search the antibodies with higher fitness in the global scope, so as to avoid falling into the local optimal solution.

Step 7. Termination of the algorithm

Go back to step 4 for cyclical computations until they meet the conditions of the algorithmic termination.

This paper adopts the stated maximum evolution generations combining the above formula as algorithmic termination criteria: $\left|F^* - F_{best}\right| < \varepsilon$

In this formula, ε is the given penalty, F^* is the global optimal solution, F_{best} is the best antibody's fitness in the current evolution generation

Simulation

To verify the effectiveness of the proposed algorithm, take the economic development demand and power load forecast of a certain region for instance. There are currently 10 power plants with a total capacity of 5.9GW (see Table 1 for the main parameters); 8 power plants to be set up (see Table 2 for main parameters). Load growth within the planning period of a system is shown in 3[5].

To verify the superiority of the proposed algorithm, Table 4 shows the comparison between improved immune algorithm and other algorithms in optimal target value and running time, which indicates that either from the point of calculation time or target functions, the proposed improved algorithm is superior to other algorithms.

Table 1 Main parameters for current power plants

Type	*Number of installation sets*	*Capacity of single set*	*Base-load coal consumption*	*Peak-load coal consumption*	*Price of coal*	*Utilization hours*	*Repair fees*	*Minimum output*	*Number of maintenance months*
A(Thermal power)	2	0.2	400	400	120	0.7	8	75	2
A(Thermal power)	5	0.3	390	390	120	0.7	8	75	2
A(Thermal power)	2	0.4	384	384	120	0.7	8	75	2
A(Thermal power)	3	0.5	360	360	120	0.7	8	75	2
B(Hydropower)	4	0.1	0	0	0	0.25	3	25	1
B(Hydropower)	2	0.15	0	0	0	0.36	3	25	1
B(Hydropower)	2	0.05	0	0	0	0.36	3	25	1
C(Nuclear power)	1	0.3	0	0	0	0.7	4	75	2
C(Nuclear power)	2	0.2	0	0	0	0.7	4	75	2
C(Nuclear power)	2	0.1	0	0	0	0.7	4	75	2

Table 2 Main parameters for power plants to be built

Type	*Number of installation sets*	*Capacity for single set*	*Base-load coal consumption*	*Peak-load coal consumption*	*Price of coal*	*Utilization hours*	*Maintenance-freight fees*	*Minimum output*	*Number of months for maintenance*	*Economic lifespan*	*Investment*	*Number of construction years*
A	4	0.4	340	340	120	0.7	8	75	2	20	0.075	2
A	4	0.3	350	350	120	0.7	8	75	2	20	0.095	2
A	4	0.5	334	334	120	0.7	8	75	2	20	0.095	3
A	4	0.6	324	324	120	0.25	3	25	1	20	0.084	2
A	4	0.7	315	315	120	0.25	3	25	1	20	0.150	2
B	2	0.2	0	0	0	0.38	3	25	1	35	0.158	4
B	3	0.1	0	0	0	0.38	3	25	1	35	0.220	4
B	2	0.05	0	0	0	0.32	4	75	2	35	0.184	5

Table 3 Load growth of system within the planning period

Years	***Load***									
	1	2	3	4	5	6	7	8	9	10
Maximum load	3 682.5	4 085.4	4 514.2	5554.4	5 987.5	6 002.4	6 465.2	6 875.2	7 006.4	7 942.8
Power consumption	15 465	21 145	22 458	24 587	26 667	30 487	34 895	37 254	39 468	46 875

Table 4 Comparison of various algorithms in calculation results

Comparison issues	*Dynamic planning algorithm*	*Hill-climbing algorithm*	*Genetic algorithm*	*Particle swarm optimization*	*Improved immune algorithm*
Target functions/ (RMB 10,000yuan)	5 852	5 747	5 462	5 335	5 298
Running time/ s	52	41	32	26	11

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