An Improved Chaos Quantum Immune Algorithm for Power Generation Expansion Planning

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Abstract. In this paper, a new chaos quantum immune algorithm is proposed, which combines the ergodicity of chaos search and the efficiency of quantum computation into the immune optimization algorithm. In this algorithm, antibodies in the algorithm population are encoded by quantum bits and replaced by quantum revolving gate. At the same time, in order to evolve the quantum bits of the corresponding phase, we introduce two different chaotic variables into the quantum revolving gate. Among them, local search is realized by using a small number of excellent clones; the excellent clone with relatively large amplitude realizes global search. The convergence of this method is verified. At the end of the paper, a simulation example is used to show that compared with the existing methods, The improved immune algorithm has a great improvement in the efficiency of solving the problem, at the same time, it also improves the convergence efficiency.

1. Introduction
Power supply planning is the extremely important research decisions in the power system. Its core problem is to find the most economical power supply solution according to the forecast of power load growth in a certain period of time within the time limit of planning and under the condition of meeting a certain reliability level, to determine when, where and what type and capacity of power plant to be built, so as to meet the demand. The demand for load growth caused by economic development is the most reasonable. [1]

According to the characteristics of the power planning problem, there are many variables in the mathematical model, and the nonlinear, nonconvex and discrete characteristics of the model. The traditional method is to use the relevant mathematical optimization methods, such as nonlinear programming, linear programming, integer programming, dynamic programming and so on. However, in order to meet the requirements of these traditional methods, they must be linearized, which will bring errors. At the same time, traditional optimization methods have some difficulties in dealing with inequality constraints. [2]

In recent years, artificial immune algorithm is an artificial intelligence optimization algorithm based on biological immune system. The objective function and feasible solution of the optimization problem are respectively corresponding to antigens and antibodies in the immune algorithm. The fitness of the feasible solution and the corresponding objective function is replaced by the affinity between antibody and antigen. And the diversity of possible solutions is guaranteed by the affinity between antibodies. By calculating the survival rate of each antibody, the antibody with high survival rate can be inherited and mutated accordingly. The memory cell unit is used to save the optimal feasible solutions to inhibit the continuous generation of similar feasible solutions and speed up the search for the global optimal solution. At the same time, when similar problems occur again, it can quickly generate the better or even
the most appropriate solutions. This algorithm is suitable for global search and is widely used in nonlinear optimization problems such as power system planning and optimal power flow calculation. [3]
To solve the power planning problem, this paper proposes an improved immune algorithm. According to the corresponding simulation results, the application of this algorithm in power planning can effectively improve the local search ability and accelerate the convergence speed.

2. Mathematical Model of Power Generation Expansion Planning
Power generation expansion planning is to minimize the cost of economic expenditure as the ultimate goal, in the whole planning period to find solutions that can meet both the demand for power load growth and the corresponding constraints. In order to facilitate the comparison, this paper uses the unified annual value method to calculate the investment cost, and considers that the annual cost is equivalent. According to the characteristics of power planning model, the objective function of this problem is defined as [1]:

$$OF_j = \sum_{i=1}^{T} \left( Z_i + O_i + Q_i - B_i - R_i \right) \left( 1 + r \right)^{-t} + \sum_{j=0}^{M} \left( F_{j} + F_{k} \right) \left( 1 + r \right)^{-T_j} + \sum_{j=1}^{M} \beta_j F_j, i=1,2,3,...,N$$ (1)

$Z_i$ is the investment cost of Project $i$ in the $t$ th year; $O_i$ is the cost of power supply loss at the end of Project $i$ in the $t$ th year; $Q_i$ is the cost of waste water and hydropower loss of Project $i$ in the $t$ th year; $B_i$ is the benefit (RMB 10,000 yuan) of hydropower and thermoelectricity (10000 yuan) except for generation plan $i$ in the $t$ th year; $R_i$ is the recovery charge of residual value of plan $i$ in the $t$ th year (RMB 10,000 yuan); $r$ is discount rate; $T_i$ is planning period of the project; $N_j$ is program set with alternative plants; $F_j$ and $F_k$ are the fixed O & M cost and fuel cost of $i$ project in $t$ th year. $M$ is the number of constraints constraint condition; $\beta_j$ is difference cost under corresponding constraint $j$; $F_j$ is the calculated value when Program $i$ cannot meet the constraint conditions.

3. Application of Improved Immune Algorithm in Generation Expansion Planning
Artificial immune algorithm is an intelligent optimization algorithm developed by imitating the principles and mechanisms of biological system to resist the invasion of external information. It simulates the mechanisms of clonal selection, cell selection, memory cell acquisition, antibody concentration regulation, etc. of immune system, Its function is mainly to solve the corresponding control problems of complex systems which are difficult to be dealt with by traditional mathematical methods. Artificial immune system is very suitable for solving these problems. It is a practical engineering problem with high requirements of adaptability, robustness and dynamic. However, for the latter problems that need to be searched in a relatively small range, the efficiency of this algorithm is not high.[2]
Chaos theory is a method of both qualitative thinking and quantitative analysis, which is used to explore the behavior that a single data relationship cannot be used in a dynamic system (such as population movement, chemical reaction, meteorological change, social behavior, etc.), but only a whole and continuous data relationship can be used to explain and predict. Chaos theory is a method of qualitative thinking and quantitative analysis. The effect of chaos optimization method is obvious in small space search, but not ideal in large space search.
Quantum evolutionary algorithm (QEA) is a new probability search method, which combines the concept and principle of quantum computation with evolutionary algorithm. Based on the concepts and principles of qubit representation, quantum state superposition, quantum logic gate operation and quantum measurement in quantum computation, this algorithm adopts a completely different representation from the traditional evolutionary algorithm, namely, qubit representation. Compared with some traditional evolutionary algorithms, quantum evolutionary algorithm has excellent global search
ability and fast convergence speed. At the same time, when the population size is small, the performance of the algorithm is not affected. [4]
Based on the above analysis, combining the probability search advantages of chaos system theory and artificial immune algorithm, and the efficiency of quantum optimization, this paper proposes an evolutionary algorithm based on Chaos Quantum immune. This improved evolutionary algorithm uses qubits to initialize the evolutionary population, adopts the method of quantum revolving gate to update the individuals, and at the same time, for the clones with better performance After amplification, the mutation of individuals with poor performance is processed, and the range of quantum rotation angle is defined respectively. On this basis, the ergodicity of the corresponding range is realized by introducing chaos variables. The simulation results show that the improved immune algorithm has the advantages of fast convergence speed and strong search ability on the basis of maintaining population diversity.[5]
Using the improved chaos quantum immune algorithm proposed in this paper to solve the Generation Expansion Planning problem:
Step 1. Fitness objective evaluation function
We use formula (1) as the objective evaluation function of fitness.
Step2. Initial population
In the process of chaos optimization, logistic map is used to generate chaos variables in chaos system:
\[ x_{n+1} = \mu x_n (1 - x_n) \]
The following \( r \) logistic map is used to generate \( r \) chaotic variables:
\[ x'_{i,n+1} = \mu x_i' (1 - x_i') \quad i = 1, 2, 3, \ldots, r \] (2)
\( \mu_i = 4 \) is a chaotic attractor, and the sequence number of the chaotic variable is \( i \). Let \( n = 0 \), give the initial value of \( r \) chaotic variables, and then \( r \) chaotic variables are obtained by formula(2), i.e. \( x_i'(i = 1, 2, \ldots, r) \). The qubit of the first antibody is used to initialize the population of the \( r \) chaotic variable to generate \( n = 1, 2, \ldots, N - 1 \), and then an additional N-1 antibodies is produced according to the method discussed above. So that the initial population of N antibodies is formed..
So, the No. \( n \) antibodies is
\[ P_n = \begin{bmatrix} \alpha_n^1 & \alpha_n^2 & \ldots & \alpha_n^r \\ \beta_n^1 & \beta_n^2 & \ldots & \beta_n^r \end{bmatrix} \] (3)
Among, \( \alpha_n^i = \cos(2^{x_i'} \pi) \), \( \beta_n^i = \sin(2^{x_i'} \pi) \).
Step 3. Solution space transformation
Each antibodies in this population \( 2r \) qubit probability amplitude. Then the \( 2r \) probability amplitude is mapped from the unit space to the solution space of the optimization problem by using the linear transformation. The probability amplitude in each antibody corresponds to an variables to be optimized in the corresponding all feasible solutions. If i qubit of \( P_n \) is \( [\alpha_n^i, \beta_n^i]^T \), the corresponding variable in the corresponding solution space is:
\[ X_{1i}^n = \frac{1}{2} [b_i (1 + \alpha_n^i) + a_i (1 - \alpha_n^i)] \] (4)
\[ X_{2i}^n = \frac{1}{2} [b_i (1 + \beta_n^i) + a_i (1 - \beta_n^i)] \] (5)
In this corresponding optimization problem, each antibody has two corresponding possibilities, \( \alpha_n^i \) among which the probability amplitude of quantum state is \( |0> \) corresponding to \( X_{1i}^n \), \( \beta_n^i \) that of quantum state and \( |1> \) corresponding to \( X_{2i}^n \), \( i = 1, 2, 3, \ldots, r; n = 1, 2, \ldots, N \).
Step 4. Individual cloning method and clone amplification method
Clone q (q < n) antibody with the highest fitness was found out from the population with N antibodies, and a new population was formed by combining the found antibody with the newly cloned antibody. We assume that the q antibody is \( P_1, P_2, \ldots, P_q \) arranged in descend order according to the fitness status.

In this way, new antibodies number is \( N_k = \left\lfloor \frac{\rho N}{k} \right\rfloor \) that is obtained by cloning antibodies \( P_k \) (1 ≤ k ≤ q).

Here, the number of antibodies [•] indicates integer operation and \( \rho \) given control parameters.

To keep the population constant, when \( \sum_{i=1}^{q} N_i < N - q \), use formula (3) to generate new antibodies and add them to the population; or add \( N - q \) antibodies to the population.

We change the quantum phase of antibodies through quantum rotation gate to achieve population individual cloning and amplification. Specifically, in the ergodic search range of the rotation angle of the quantum rotation gate, we first give the clone amplitude \( \lambda_k \), and then define the quantum rotation gate according to \( \theta_k \).

If the biphasic property appears in the ergodic range, we set the ergodic range of \( \theta_k \) as \( [\lambda_k, \lambda_k] \), when the chaotic variable \( x_{n+1} = 8x_n(1-x_n) - 1 \). If the amplification matrix is needed, the higher the adaptability is, the smaller the superimposed chaos disturbance is.

Therefore, \( \lambda_k = \lambda_0 \exp((k - q)/q) \) (\( \lambda_0 \): control parameters), it is used to control the chaotic interference of antibodies.[5]

In this case, assume that the clone matrix \( N_0.k \) is

\[
\begin{bmatrix}
\cos(\theta_1^k) & \cos(\theta_2^k) & \cdots & \cos(\theta_s^k) \\
\sin(\theta_1^k) & \sin(\theta_2^k) & \cdots & \sin(\theta_s^k)
\end{bmatrix}
\]

So, the new antibody produced by the amplification of quantum revolving gate clone, is

\[
P_k = \begin{bmatrix}
\cos(\theta_1^k + \Delta \theta_1^k) & \cos(\theta_2^k + \Delta \theta_2^k) & \cdots & \cos(\theta_s^k + \Delta \theta_s^k) \\
\sin(\theta_1^k + \Delta \theta_1^k) & \sin(\theta_2^k + \Delta \theta_2^k) & \cdots & \sin(\theta_s^k + \Delta \theta_s^k)
\end{bmatrix}
\]

(\( s = 1, 2, 3, \ldots, N_k \))

From the clone amplification of the above optimal antibodies, we can find that the selected optimal antibody has the function of optimizing coordinates, and by introducing chaos variables in a small range, the ergodicity of the local optimization of the algorithm is enhanced.

Step 5. Poorer antibodies mutation surgery

After clone amplification, the solution space is transformed into the corresponding population, and then the fitness of each antibody is calculated. On this basis, the quantum phase of the antibody is disturbed by the quantum rotating gate, so the mutation operation of m (m < N) antibody with low fitness is realized.

Firstly, we define a variation amplitude \( \lambda_k \) which is the rotation angle range of the quantum rotation gate. Then we introduce chaos variable to determine the rotation angle of the quantum rotation gate. Therefore, we can draw the corresponding conclusion: the lower the individual adaptability is, the greater the chaos disturbance is. Then, the m antibody with the lowest fitness selected is arranged according to the order of increasing fitness. Here, the mutation amplitude of k matrix is \( \lambda_k = \lambda_0 \exp((m - k)/m) \), and \( \lambda_0 \) is the control parameter to control the intensity of chaos disturbance.

Generally, \( \lambda_0 = (5 \sim 10) \lambda_0 \) is used, and the range of rotation angle is \( [\lambda_k, \lambda_k] \)

Step 6. Production of new antibodies

According to the fitness, the cloned and mutated populations were classified, and the new antibody produced by formula (3) was used to replace the relatively low fitness \( d(d < n) \) antibody. Its operation process is to search the whole feasible solution space in chaos, It is to find the antibody with strong adaptability in the global scope, so as to avoid falling into the local optimal solution.

Step 7. Termination conditions of algorithm

Turn back to step 4 for the same calculation until the algorithm meets the termination conditions.
The termination condition of the algorithm used in this paper is the combination of the maximum evolution generation and the following formula: $|F^* - F_{best}| < \varepsilon$

In this formula, $\varepsilon$ is the sentencing, $F^*$ is the global optimal feasible solution, $F_{best}$ is the best adaptability of antibody in current evolution generation.

4. Simulation and Conclusion

We take the actual demand of the social and economic development of a certain region and the power load forecast of that region as an example to verify whether the corporate algorithm proposed in this paper is effective. There are 10 power plants in the area with a total capacity of 5.9gw (see Table 1 for relevant parameters); in addition, 8 new power plants are planned to be built (see Table 2 for relevant parameters). Meanwhile, the power load growth forecast of the region during the system planning period is shown in 3[5].

In order to verify the superiority of this algorithm, Table 4 shows the comparison between the improved immune algorithm and other algorithms in terms of optimal target value and running time. The results show that the improved immune algorithm is better than Linear programming algorithm, Simulated annealing algorithm, genetic algorithm, Ant colony optimization and other algorithms to solve power planning problems in calculation time and objective function.[1]

Table 1. Control parameters of existing power plant

| Type           | Number of installation sets | Single unit capacity | Coal consumption at base load | Coal consumption during peak period | 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                           |
| B (Hydroelectric)  | 3                           | 0.13                 | 0                             | 0                                 | 0             | 0.31              | 4           | 30             | 2                           |
| B (Hydroelectric)  | 1                           | 0.16                 | 0                             | 0                                 | 0             | 0.36              | 4           | 30             | 2                           |
| B (Hydroelectric)  | 1                           | 0.07                 | 0                             | 0                                 | 0             | 0.36              | 4           | 30             | 2                           |
| C (Nuclear energy) | 2                           | 0.31                 | 0                             | 0                                 | 0             | 0.6               | 5           | 65             | 3                           |
| C (Nuclear energy) | 1                           | 0.22                 | 0                             | 0                                 | 0             | 0.6               | 5           | 65             | 3                           |
| C (Nuclear energy) | 1                           | 0.12                 | 0                             | 0                                 | 0             | 0.6               | 5           | 65             | 3                           |

Table 2. Control parameters of the new power plant.

| 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                     | 342                       | 342                      | 125           | 0.7               | 8                      | 76             | 2                            | 0.076            | 2         |                             |
| A    | 4                           | 0.3                     | 352                       | 352                      | 125           | 0.7               | 8                      | 76             | 2                            | 0.0965           | 2         |                             |
| A    | 4                           | 0.5                     | 334                       | 334                      | 125           | 0.7               | 8                      | 76             | 2                            | 0.096            | 3         |                             |
| B    | 2                           | 0.2                     | 0                         | 0                        | 0             | 0.38              | 3                      | 25             | 1                            | 0.158            | 4         |                             |
| B    | 3                           | 0.1                     | 0                         | 0                        | 0             | 0.38              | 3                      | 25             | 1                            | 0.220            | 4         |                             |
| B    | 2                           | 0.05                    | 0                         | 0                        | 0             | 0.32              | 4                      | 75             | 2                            | 0.184            | 5         |                             |
Table 3. System load growth in planning period.

| Years | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10  |
|-------|----|----|----|----|----|----|----|----|----|-----|
| Load  | 3683.5 | 4086.4 | 4514.3 | 5554.4 | 5986.5 | 6002.4 | 6466.2 | 6876.2 | 7006.4 | 7942.8 |
| Power consumption at maximum load | 15467 | 21146 | 22457 | 24587 | 26668 | 30487 | 34875 | 245245 | 39468 | 46875 |

Table 4. The advantages and disadvantages of different algorithms.

| Comparison issues | Linear programming algorithm | Simulated annealing algorithm | Genetic algorithm | Ant colony optimization | Improved immune algorithm |
|-------------------|-------------------------------|-------------------------------|-------------------|-------------------------|---------------------------|
| Target functions/ (RMB 10,000 yuan) | 5 854 | 5 746 | 5 463 | 5 336 | 5 312 |
| Running time/ s    | 53  | 47 | 31 | 25 | 12 |

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