Voltage control strategy based on immune particle swarm optimization algorithm

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Received 1 June 2014, www.cmnt.lv

Abstract

As a new swarm intelligence algorithm after Ant Colony Algorithm (ACA), Immune Particle Swarm Optimization (IPSO) is currently an important branch of evolutionary algorithm. Its basic idea is influenced and inspired by research results of their modeling and simulation of behaviors of swarms of birds in earlier periods. And their model and simulation algorithm mainly took use of biologist FrallkHeppner's model. Though PSO algorithm has been effectively applied in many areas, it has a short development history and problems exist in global convergence. Because IPSO Algorithm has the characteristics of loose mathematical condition, fast convergence speed and simple programming, this paper tries to minimize transformer loss using the IPSO algorithm, providing a new method to solve the automatic voltage control problem (AVC problem).

Keywords: IPSO Algorithm, Voltage Control, AVC Problem

1 Introduction

PSO Algorithm, since its appearance, has quickly aroused concerns from international scholars in related fields. Kennedy J and Eberhart R.c. first put forward binary PSO algorithm and then in order to improve the convergence of the algorithm, in 1998 Shiy and Eberhart R.C. brought in inertia weight parameters and put forward that in the evolution process, dynamically adjusted inertia weight to balance the speed of convergence. This evolutionary equation was called standard PSO algorithm, after then LDW-PSO algorithm (Linear Decreasing Weight PSO) appeared. Currently, improvements on PSO algorithm are mainly as follows, first, various advanced mechanisms were brought in in PSO algorithm and researches were carried out on improved PSO algorithm; second, a good combination of PSO algorithm with other intelligence optimization algorithm to specialize in the study of various hybrid algorithm to complement each other for improvement of algorithm performance.

In recent years, with the development of the hydropower plant automation technology, hydropower station computer monitoring system could calculate out the decreased or increased reactive power value required for the whole factory online according to the real-time monitoring of bus voltage value. And through the corresponding control system, automatically increase or decrease reactive power value of generator sets, making sure the hydropower station bus voltage maintain in a certain range for the secure, stable and economic operation of the power system.

This paper would combine the general PSO algorithm to form IPSO algorithm based on Logistic and Tent mapping. Taking one power plant as an example, its AVC control method would be as follows: work out the reactive power value to keep bus voltage in a certain range adopting the method of sensitivity analysis and at the same time allocate the reactive power reasonably to each generator set. From this, we can see this method has the excellence of swift and accurate adjusting and also in considerate of the active power loss problem of the power plant.

2 Immune particle swarm optimization algorithm

2.1 THE BASIC PRINCIPLES OF IPSO ALGORITHM

IPSO algorithm is a complex algorithm in combination of immune algorithm and PSO algorithm, it uses antigen as the problems to be solved, antibody as the solution and at the same time each antibody is one particle of the particle swarm. The affinity between antigen and antibody is measured with the fitness in PSO algorithm, reflecting the satisfaction level of objective function and restraint conditions. The affinity between antibodies reflect the difference between particles, namely the diversity of particle swarms. By the immune selection mechanism based on concentration and antibody expected life cycle, to promote high fitness antibodies (particles) and inhibit antibodies (particles) of excessive concentration, ensuring the convergence of the algorithm and diversity of the swarms. Meantime, each particle has its own speed and its position and knows individual extremum and global extremum. In iterative evolution, the particles (antibodies), by following individual extremum and global extremum, make population evolution has a clear

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direction-the population converging in the direction of optimal solution , to speed up the algorithm convergence speed [1].

2.2 THE PROCEDURE OF IPSO ALGORITHM

Usually, IPSO algorithm has the following steps:
S*tep 1* Initialize Parameter: Initialize population size, evolutionary algebra, antibody similarity coefficient, mutation rate, the weighted coefficient of PSO algorithm, learning factor etc
Step 2 Initialize population: Initialize antibody (particles) population, if the system has once worked out the similar problems, then it would refer to the memory antibodies of such sort of problems as initial solutions, or else it would give the initial position and velocity meeting the requirements.
Step 3 Evaluate Population: Construct the fitness function, calculate the adaptive value and repulsive force between antibodies (particles) and get the expected lifetime of antibodies (particles).
Step 4 Population Evolution: Construct appropriate immune operator, through like crossover and mutation, generate antibodies (particles) swarms of next generation.
Step 5 Immune selection: Priority to breed antibodies having greater affinity with antigens, inhibit antibodies of high concentration and eliminate those of low affinity.
Step 6 Population Renewal: Renew velocity and position of each particle. Replace individuals of low fitness level with those of high fitness level in memory population and form antibody population of the next generation.
Step 7 Termination: Test whether meet the ending conditions, if the current iteration number has reached the maximum number of iterations, or error reached the minimum requirements, then stop iteration and output the solution, otherwise go back to step 3. Referring to IPSO algorithm in some literature, keep the diversity of population based on the concentration of immune selection and immune memory, but no operation of crossover and mutation. Algorithm with crossover operation finds less iteration number optimal solution than algorithm without crossover operation, and such algorithm has relatively stable evolution process. Mutation operator could increase new search space, improve the algorithm's search ability and keep the diversity of population. Some other documents also mentioned IPSO algorithm based on clonal selection, in the evolution process, the introduction of the clone copy operator, clone selection operator and clone high-frequency mutation operator could enhance the diversity of population, but it could result population degradation without vaccine extraction and vaccination strategies, and guidance of crossover and mutation [2,3].

3 Improved IPSO algorithm

The improved IPSO algorithm talked in this paper, on the basis of the existing PSO algorithm, through crossover and high frequency mutation operation , to ensure the diversity of population evolution and overcome the premature phenomenon of PSO algorithm. The algorithm's global searching ability is improved through Cauchy mutation, and local searching ability is improved by Gauss mutation. In addition, the introduction of the vaccine extraction and immunization strategy is to solve possible degradation caused by random crossover and mutation operation without guidance [4]. Figure 1 is improved IPSO algorithm model:

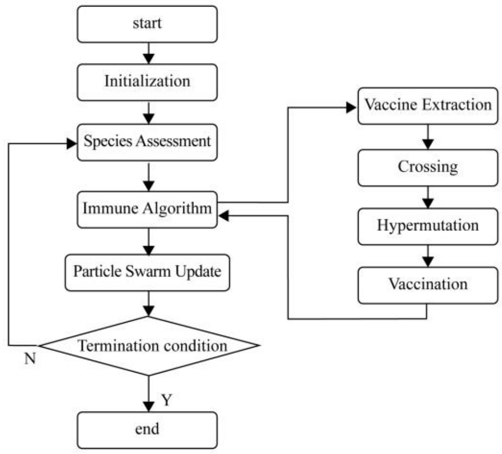

FIGURE 1 Improved IPSO algorithm model

3.1 THE CALCULATION PROCESS OF IMPROCESS OF IMPROVED ALGORITHM

3.1.1 Population evaluation

The antibody should be evaluated specifically to each condition. For testing algorithm performance optimization function, the antibody can be evaluated according to the function value. In order to guarantee the diversity of antibody population and avoid premature convergence, this paper uses antibody survival expectation to adjust the concentration. The greater the affinity between the antibody and antigen, the higher of the antibody survival expectations; the greater of the concentration of the antibody, the lower of the antibody survival expectations. Among them, the calculation of the affinity between the antibody and antigen should be decided on the problems to be solved. The selection principle should be the better solution, the greater the affinity. The affinity between antibodies can be calculated according to the Euclidean distance. The shorter the Euclidean distance between antibodies, the more similar they are and the greater the affinity between them. The concentration of antibody are related with the affinity between one antibody with other antibodies. Antibody similarity coefficient can be defined as η ,when the ratio of the affinity between antibodies to the largest antibody affinity is greater than η , we think the two antibodies are similar, otherwise they are dissimilar. And the more of similar antibodies, the greater of the concentration of the antibody[5].

3.1.2 Vaccine extraction

The process of extracting vaccines is like this: select two antibodies having the highest survival expectation, make crossover operation and pick up the common gene segments, as a vaccine and after the treatment, join the vaccine set V. In the early evolutionary period, each components of particle are generated randomly and thus it is difficult to have a higher concentration on a certain gene segment, but with the particle flying in the direction of the optimal solution, the concentration of individual gene segments of the optimal solution in the particle swarm will increase[6].

3.1.3 Crossover and Mutation Operation

Crossover operation is the main operation of genetic algorithm, but crossover operation is not introduced in immunization program in some literatures. But from literature, through experiments, algorithm with crossover operation could find lower iterations of the optimal solution than algorithm without crossover operation, and the evolutionary process is relatively stable, so this paper still uses the crossover operation.

This paper uses Gaussian and Cauchy mutation. Cauchy mutation could to a greater probability produce large mutation value so that it could search the optimum solution in a larger space to avoid the algorithm be stalled in local extremum and improve the global search ability. The individuals of low fitness value can adopt long-step Cauchy mutation. When the searched solution is close to global optimal solution, long-step Cauchy mutation is easy to jump out of the good area and produce worse offspring, and at this time Gauss mutation should be adopted[7].

Gauss mutation could to a greater probability produce small mutation value, it has better search capability on a small scale, through small-step constantly self adapting adjusting to gradually approach global optimal solution. For excellent individuals, small-step Gauss mutation can be adopted to minimize the distance between the individual and the global optimal solution to a certain extent and thus achieve better accuracy. Cauchy mutation formula is:

$$\begin{aligned} x_i'(j) &= x_i(j) + \sigma_i'(j) \cdot C_j(0,1) \\ \sigma_i'(j) &= \sigma_0(j) \cdot e\lambda \cdot \frac{aff_{x_i} - aff_{\arg}}{aff_{\max} - aff_{\min}} \\ \sigma_0 &= \xi_1 \cdot L \end{aligned} \quad (1)$$

3.1.4 Vaccination

Crossover and mutation operator revises individuals under the condition of a certain probability distribution. As a result, it provides opportunities for the evolution of species, while inevitably produces the possibility of degradation. To solve this problem, this paper adopts the vaccine extraction and vaccination strategy, effectively using the obvious and basic feature information and knowledge of the problems to be solved to avoid possible degradation as a result of random crossover and mutation operation. Vaccine extraction process is like this: Operate crossover for the current two optimal antibodies, the resulting public part is vaccine and each vaccine is a part of the solution. The probability is about 80% for such part of solution as one part of the global optimal solution[8].

3.1.5 Particle swarm renewal

Renewal operation of particle swarm includes position and velocity renewal. Velocity Renewal formula is:

$$V_{id}' = V_{id} \oplus \partial(P_{id} - X_{id}) \oplus \beta(P_{gd} - X_{id}) . \quad (2)$$

Among them, α , β , $(\alpha, \beta \in [0,1])$ is learning factor, X_{id} , the current position for antibody X_i , P_{id} ,the antibody X_i , the individual extremum, and P_{gd} ,Current global extremum. The larger the value of α , the greater the impact of the individual extremum on velocity ; Similarly, the larger the value of beta, the greater the impact of global extremum on velocity. Particle position renewal equation is:

$$X_{id}' = X_{id} \oplus V_{id}' . \quad (3)$$

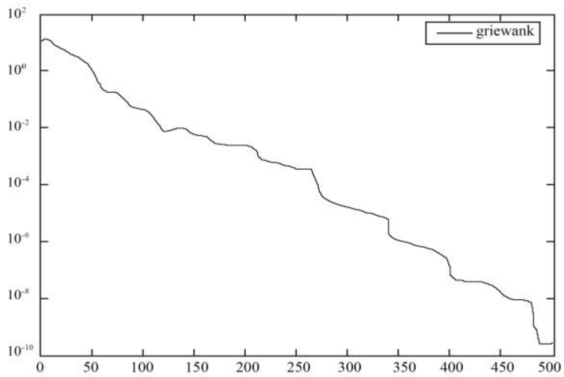

FIGURE 2 Evolution curve for griewank function minimum value

3.2 EFFECTIVENESS DEMONSTATION OF IMPROVED ALGORITHM

The Griewank function is:

$$\frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\frac{x_i}{\sqrt{i}} + 1, x \in [-600, 600] \ . \quad (4)$$

In the interval [-600,600], Griewank function minimum value is 0.The below picture is the testing result of the algorithm of this paper:

Figure 2 Sphere function

$$f_1(x) = \sum_{i=1}^{n} x_i^2, x \in [-100,100]. \quad (5)$$

Sphere function, in the interval [-100,100], minimum value is 0. The below picture is the testing result of the algorithm:

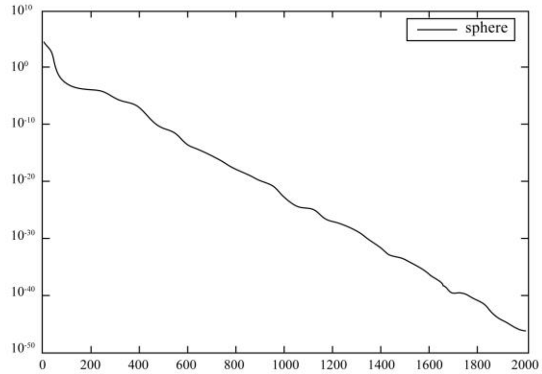

FIGURE 3 Evolution curve for griewank function minimum value

4 Simulation result of improved algorithm

In order to verify the proposed algorithm in solving the problem of automatic voltage control and its feasibility, this paper uses the general PSO algorithm, PSO-Immune algorithm respectively based on Logistic mapping and Tent mapping. Take one power plant as an experimental example, this power plant has the comprehensive benefits of power generation, flood control and navigation. Because power plant AVC system, on the basis of the optimal combination and load distribution determined that day by AGC system, is then optimal distributed by reactive power, thus the paper adopts the improved binary PSO algorithm, making optimal distribution of active power over the 24 hours of the day. The active load of the 24 hours period as shown in Table 1.

TABLE 1 The active load of the 24 hours period of one day in the power plant

Time	1	2	3	4	5	6	7	8	9	10	11	12
Load (Mvar)	550.36	551.21	551.40	551.87	551.45	551.63	551.48	551.15	648.46	763.41	758.37	761.42
Time	13	14	15	16	17	18	19	20	21	22	23	24
Load (Mvar)	761.35	761.47	761.56	761.37	758.37	761.36	826.68	830.45	830.37	791.47	763.47	761.47

Getting from the AGC system the 24 hours period the optimal set combination and load distribution by, on the basis of which carry on simulation calculation actual reactive power for stabilizing busbar voltage. Reactive power transmission over the 24 hours of a day as shown in Table 2.

TABLE 2 Reactive load table over the 24 hours period of a day in the power plant

Time	1	2	3	4	5	6	7	8	9	10	11	12
Load (Mvar)	500	512.6	458.3	291.6	340.2	335.7	493.6	517.3	410.6	526.1	515.5	591.8
Time	13	14	15	16	17	18	19	20	21	22	23	24
Load (Mvar)	638.5	511	647.5	668.1	711.3	503	657.2	503.6	373.2	621	585.4	615

Set the population size of PSO algorithm, N = 30, evolution number M = 600, immune local search number C = 200, learning factor $c_1 = c_2 = 2.05$, particle maximum flight speed $V_{\max} = 4.0$.

The encoding of particles uses the reactive power value of set per time, regardless of shutdown set. Provided the initial conditions are identical, carry out the simulation calculation adopting the general PSO algorithm, IPSO algorithm respectively based on Logistic mapping and Tent mapping. In the case of continuous calculation of 100 times, compare separately the optimal solution, the average solution, the average computation time and standard deviation, as shown in Table 3.

TABLE 3 Comparison of transformer active loss using different algorithm (Unit 10 Thousand Kw)

Algorithm Type	The optimal Solution	Average Solution	Average Calculation Time(s)	Standard Deviation
Basic PSO algorithm	40.2958	40.3279	28.6473	0.063748
IPSOalgorithm based on Logistic mapping	40.2421	40.2618	35.4677	0.006462
IPSOalgorithm based on Tent mapping	40.2373	40.2476	31.3638	0.002478

According to the above table, in AVC algorithm, the IPSO algorithm optimization result is better than general PSO algorithm; In the process of using PSO-Immune algorithm for solution, IPSO algorithm based on Tent mapping for the optimal solution, average solution, calculation time and standard are better than IPSO algorithm based on Logistic mapping, this is because of the close relationship of Tent mapping and Logistic mapping distribution characteristics in their respective immune mapping interval.

The immune sequence from Tent mapping equation reflects characteristics of uniform distribution in the mapping space, while Logistic mapping focuses more on the both ends of the interval. And the optimal solution obtained from this paper's experimental calculation, the optimal value of reactive power of each sets are not in their respective reactive power limit point, but in the interval of upper and lower limit. Therefore, compared to Logistic mapping for its distribution characteristics, Tent mapping's uniform distribution characteristic in the mapping space would be more favorable for IPSO algorithm to find the global optimal solution. The 50 set of solutions obtained from IPSO algorithm based on Tent mapping have lower standard deviation and shorter calculation time than IPSO algorithm based on Logistic mapping, which also suggests that the solving result is more stable and global optimization efficiency is higher.
Iteration using PSO algorithm, IPSO algorithm respectively based on Logistic mapping and Tent mapping, get convergence curve as shown in Figure 4.

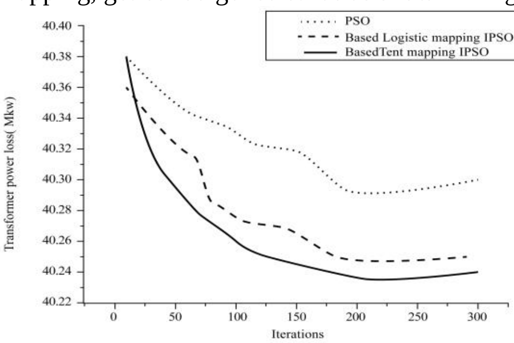

FIGURE 4 Convergent characteristic comparison using the three types of algorithm

From the above convergent characteristic comparison picture using the three types of algorithm, in terms of convergence speed, general PSO algorithm converge to the optimal solution iterating about 150 times, while 200 times for IPSO. From the respect of getting the optimal results, IPSO could effectively jump out of local optimal solution and thus its global optimization ability is stronger than general PSO algorithm; IPSO algorithm based on Tent mapping is better than algorithm based on Logistic mapping.

5 Conclusion

This paper studies the basic theory and the solving method for automatic voltage control and achieves some applicable result. The proposed algorithm has the excellence of swift and accurate process adjusting. As for the whole power grid, a single node reactive power research could no longer satisfy the needs of the running of the whole power system voltage control and economic operation, further research is needed on the theory and method of automatic voltage control of power system.

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