Analyze Comparison Research on Three Biological Evolution Algorithms

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Abstract
As typical evolutionary algorithms, Artificial immune lgorithm, Genetic algorithm and Bee Colony algorithm have their own advantages. This paper introduced the basic knowledge of evolutionary algorithms, and detailed respectively descriped the characteristics of three algorithms, including how to be proposed, features and algorithm steps. Then in this paper, meta task scheduling and intelligent optimization algorithms in grid resource scheduling were as test method, under different parameters conditions analyzed and compared the performance of three algorithms. At last the comparison result was given.
Keywords: ARTIFICIAL IMMUNE ALGORITHM, GENETIC ALGORITHM, BEE COLONY ALGORITHM.

1. Introduction

Evolutionary algorithm, or evolutionary algorithm, is a cluster algorithm. Although it has a lot of changes, different genetic expression, different crossover and mutation operator, a special operator references, and various regeneration and selection methods, but their inspiration comes from the nature of biological evolution [1].

Compared with traditional methods based on calculus and exhaustive method optimization algorithms, evolutionary computing is a mature with high robustness and broad applicability of global optimization method, has self-organizing, adaptive and self-learning characteristics; It cannot limit by the nature of the problem, to deal complex problems effectively which traditional optimization algorithm is difficult to solve.

Evolutionary algorithm is based on Darwin's theory of evolution by simulating biological evolution process and mechanism for solving the problem of self-organizing, adaptive artificial intelligence technology. Biological evolution is by breeding, mutation, competition and choice to achieve; evolutionary algorithm for solving optimization problems mainly through selection, recombination and mutation of these three operations, as shown in Fig. 1.

Evolutionary algorithms including genetic algorithms, genetic programming, evolutionary programming and evolutionary strategies, etc. The basic framework of evolutionary algorithms or simple genetic algorithm framework described, but there are large differences in the evolution of the way [2]. Selection, crossover, mutation, population control, there are a lot of changes [3].

In the follow chaptors, meta task scheduling and intelligent optimization algorithms in grid resource scheduling were as test method, under different parameters conditions analyzed and compared the per-

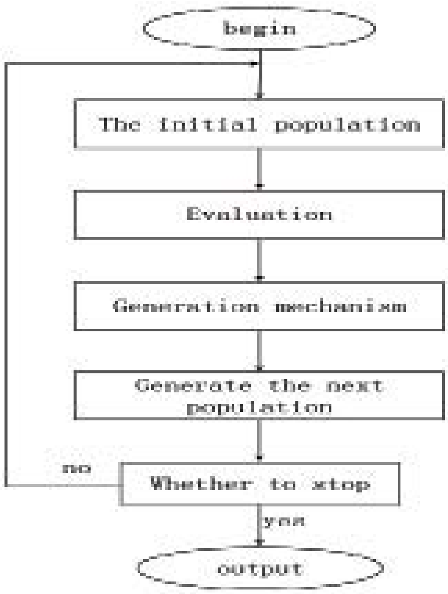

Figure 1. The basic flow chart of evolutionary algorithm

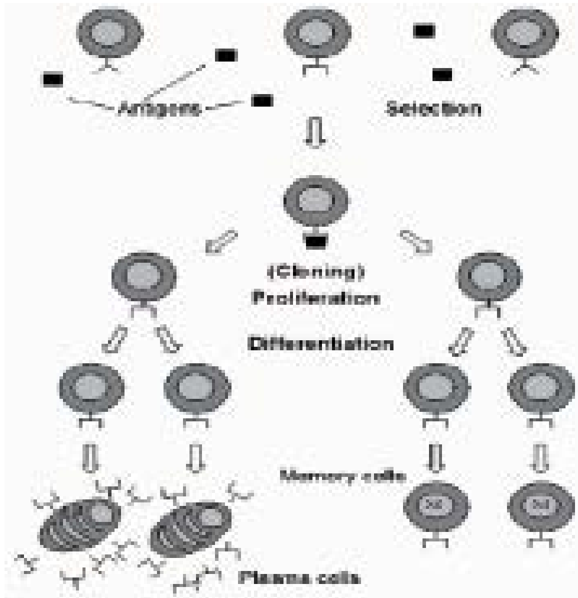

Figure 2. The clonal selection theory pattern

formance of three algorithms. At last the comparison result was given.

2. Immune Algorithm

Biological immune system is a distributed, self-organization and has the dynamic equilibrium ability of complex adaptive systems. With a strong pattern classification capability, particularly the analysis of multi-modal issues, handling and solving showed high intelligence and robustness [4].

Clonal selection is a dynamic process of the adaptive immune system organism antigen stimulation, as shown in Fig 2. This process reflects the biological characteristics of the current learning, memory, antibody diversity [5]. It is artificial immune systems learn from.

From the perspective of biological information processing point of view, it can be classified as information science category, with artificial neural networks, Evolutionary Computation and other intelligence theory and methods of parallel [6].

Immune algorithm is the learning algorithm based on the immune system; it is one of the main Artificial Immune System [7]. It has good system responsiveness and autonomy, for interference has the strong ability to maintain a self-balancing system. In addition, immune algorithm also simulates the immune system's unique learning, memory, recognition and other functions, with strong pattern classification capabilities [8], particularly the analysis of multi-modal issues, handling and solving showed high intelligence and robustness.

As shown in Fig. 3, artificial immune algorithm can generally be divided into the following basic steps [9]:

1) The definition of antigen: usually the problem to be solved or the optimal results can be achieved in the abstract becomes artificial immune algorithm antigen.

2) The definition of antibodies: a point (or a solution) in solution space corresponds to an antibody of immune algorithm.

3) Generate an initial antibody groups: general use similar methods of genetic algorithm, randomly generated initial population of antibodies.

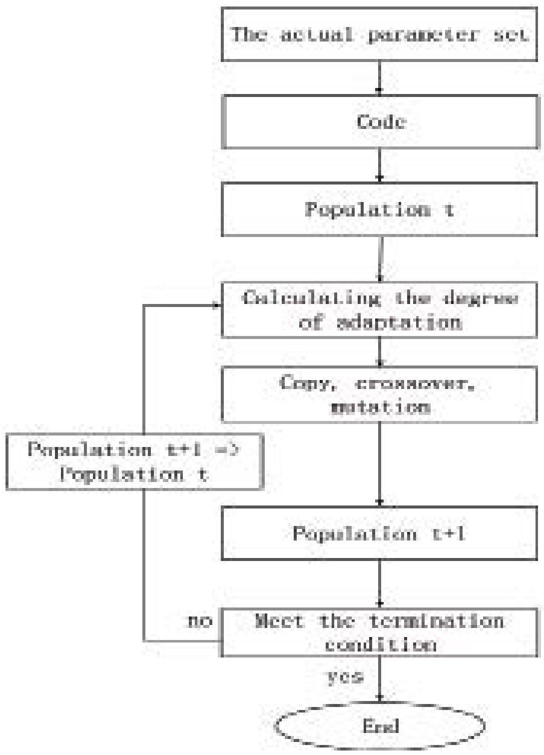

Figure 3. Genetic algorithm basic flow chart

4) Calculate the affinity: affinity include the affinity of the antibody to the antigen and the affinity between affinity and affinity. Affinity antibodies generally used to express the degree of matching or similar degree or other antibodies to the antigen, the antibody is a reflection of the merits of the evaluation value level is an important indicator to guide the evolution of the development of antibodies [10].

5) Calculate the concentration or diversity: concentration or diversity of antibody mainly used to assess population abundance patterns, provide the basis for the algorithm to guide the subsequent immune behavior (operations).

6) Various immune behaviors (operation): These immune behavior (operations) include selection, clonal variation, autologous tolerance antibody supplementation. These immune behavior (operations) are usually considered antibody affinity and concentration (or diversity) and other indicators as part of its actions (or operations) guidance (or parameters).

7) Check the termination condition: determine antibody affinity maturation population has reached, successfully identified the target antigen. Yes, end the algorithm running; otherwise, the next generation of antibody groups goes to step 4, to start a new round of iterative process until the algorithm termination condition is satisfied [11].

3. Genetic Algorithm

Genetic Algorithm is calculated biological evolution model to simulate the Darwinian mechanism of natural selection and genetics of biological evolution, is a method of searching the optimal solution by simulating the natural evolutionary process [12]. Genetic algorithm is potentially the beginning of the representation of the solution set from a population.

Basic operations of Genetic algorithm is as follows [13]:

a) Initialization: Setting evolution generation counter t = 0; set the maximum evolution generation T; randomly generated M individuals as initial population P (0).

b) Individual evaluation: Calculate the fitness of each individual in group P (t).

c) Select the operation: apply the selected operator to groups. The purpose of choice is directly inherite the optimize individual to the next generation, or create new individuals by matching and cross, and then inherite to the next generation. The selecting operation is based on the fitness of the population.

d) Cross-operation: apply the crossover operation to groups. In GA playing a central role is the crossover.

e) mutation operation: applyt the mutation operator to groups. That is, to make changes to the population genetic value of individual strings certain locus.

After selection, crossover, mutation operation, group P (t) obtains the next generation of population P (t + 1).

f) Termination condition: if t = T, output the evolution obtained with the largest individual fitness as optimal, terminate the calculation.

4. Bee Colony Algorithm

Bee Colony Algorithm is a kind of optimization algorithm based on bee swarm intelligence search behavior in 2005 proposed by British scholar D T Pham. Study on the colony algorithm although is in the initial stage, but due to its less control parameters, robustness and strong adaptability, simple calculation and other advantages, has been more and more attention of scholars. Artificial bee colony algorithm has three important parts: lead the bee, following bee and investigation nee. The three part plays an important role in different stages. Lead bee and following bee update food source location according to the formula (1):

$$v_{ij} = x_{ij} + r_{ij} \cdot (x_{ij} - x_{kj}) \tag{1}$$

Selection probability is Calculated by formula (1):

$$P_i = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \tag{2}$$

$$x_i^j = x_{\min}^j + rand(0,1) \cdot (x_{\max}^j - x_{\min}^j) \tag{3}$$

Of formula (2), fit_i is the fitness value of the i solulation. Formula (3) is randomly generated a new solution, instead of being eliminated thesolution. The main process of artificial bee colony algorithm is briefly introduced in the following:

First step: initializing population is $x_i, i = (1, 2, ..., n)$. At the same time calculate for eachinitial population fitness value solution;

The second step: the lead bee search neighborhood according to formula (2), to generate the new solulation v_i, and calculate its fitness value;

The third step: compare the fitness value of v_i and the fitness value of x_i, considering whether to retain x_i;

The fourth step: according to the formula (2) calculate the relevant probability values P_i;

The fifth step: the following bee choose the food source (solution) by P_i, and according to formula (1) search neighborhood, create new solution v_i, calculate the fitness value;

The sixth step: determine the solution of satisfaction, decided whether to produce a new scouts x_i to replace it according to equation (3);

The seventh step: keep the current best solution.

The eighth step: to determine whether they meet the terminating condition of the loop, such as to meet the output of the optimal results, otherwise the reversal of the second step.

With other global optimization algorithm, artificial bee colony algorithm also exist in the traditional prone to premature convergence and low convergence speed problem in complex function optimization process. According to these problems, some scholars improved artificial bee colony algorithm.

5. Experiment and Result Analysis

5.1. Problem Description

Grid is the third internet revolution following the traditional Internet and Web technologies. Wherein meta task scheduling and intelligent optimization algorithms often applied research combined. In order to more accurately reflect the true grid computing environment, firstly related concepts of scheduling problems of grid computing task are defined as follows:

Definition 1: The grid environment G: $G=\{\mathrm{T},\mathrm{R}\}$, of which $T=\{\mathrm{t}_1,\mathrm{t}_2,...,\mathrm{t}_n\}$ represents the set of n meta tasks; $R=\{\mathrm{r}_1,\mathrm{r}_2,...,\mathrm{r}_n\}$ represents the set of n heterogeneous computing resources.

Definition 2: The execution time $\mathrm{t(i,j)}$: $\mathrm{t(i,j)}$ represents the total execution time of task t_i and resource r_j, then

$$t(\mathrm{i,j})=\frac{S(\mathrm{i})}{B(\mathrm{j})}+\frac{L(\mathrm{i})}{P(\mathrm{j})}+d(\mathrm{i,j}) \tag{4}$$

$S(\mathrm{i})$ is the size of task t_i;

$L(\mathrm{i})$ is the length of task t_i;

$d(\mathrm{i,j})$ is the communication delay of task t_i and resource r_j;

$B(\mathrm{j})$ is the bandwidth of resource r_j;

$P(\mathrm{j})$ is the computing power of resource r_j.

Definition 3: The assignment matrix $M_{i,j}$: $M_{i,j}$ represents the assignment matrix of meta task and resource. If task t_i is assigned to resource r_j, then $M_{i,j}=1$, otherwise $M_{i,j}=0$.

5.2. Result Analysis

Many scholars have done a lot of research work on the grid task scheduling algorithm. The more classic are: Genetic algorithm, Min-min algorithm, Max-min algorithm, Bee Colony algorithm, SA algorithm, Co-RSBF algorithm. In the following experiments, the paper by setting different meta number of tasks m and the number of different computing resources n, from the response time, task completion time and overall survival of the population in three areas, Immune algorithm, Genetic algorithm and Bee Colony algorithm are performed comparative experiment.

Fig. 4 and 5 show the comparison of response time of tasks under different task number of Immune algorithm, Genetic algorithm and Bee Colony algorithm. Fig. 6 and 7 show the comparison of the response time in the case of different resource nodes of Immune algorithm, Genetic algorithm and Bee Colony algorithm. Fig.8 and 9 show the comparison of execution time under resource nodes. Fig. 10 and 11 show the comparison of execution time in the case of resource nodes and the number of tasks identified. Fig. 11 and 12 reflects the contrast of the population to survive in case of resource nodes and the number of tasks identified of three scheduling algorithms.

Fig. 4 and 5 shows the response time comparison results under different number of tasks. Immune algorithm response time in most cases is minimal. The Genetic algorithm performance was relatively poor performance in terms of response time increasing the number of tasks in the whole case. When the resource

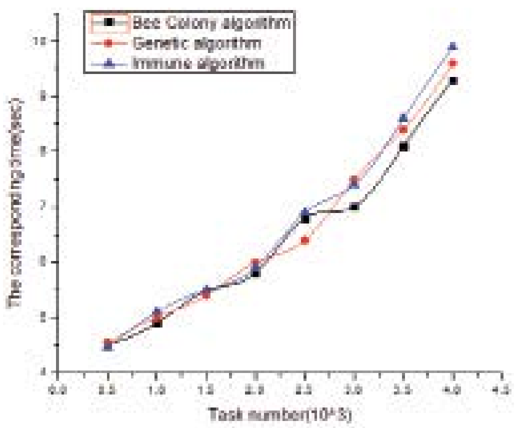

Figure 4. The corresponding time result of three algorithms (n=100)

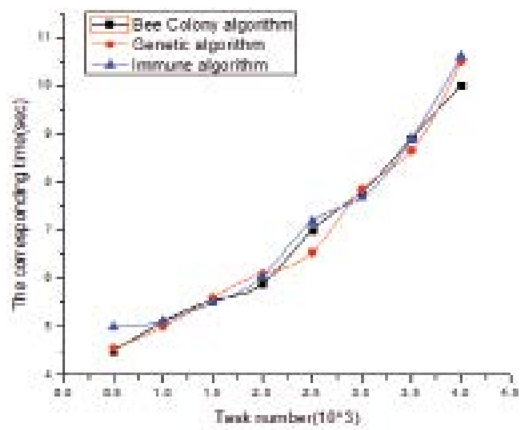

Figure 5. The corresponding time result of three algorithms (n=150)

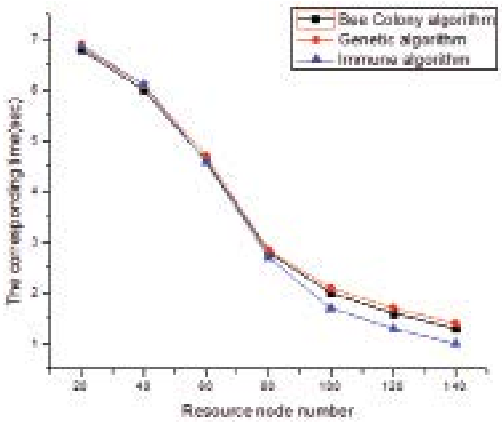

Figure 6. The corresponding time result of three algorithms (m=30000)

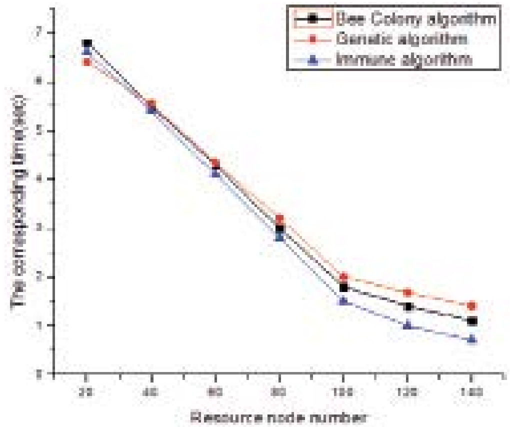

Figure 7. The corresponding time result of three algorithms (m=20000)

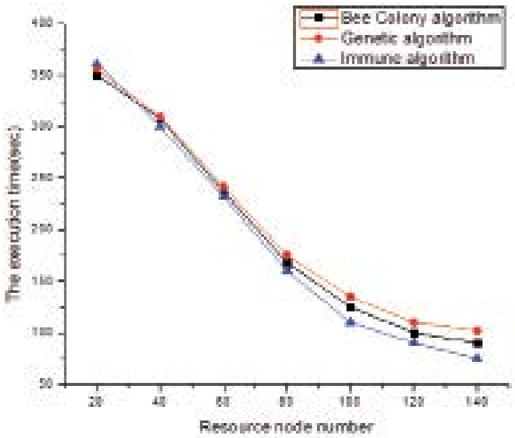

Figure 8. The execution time (sec) result of three algorithms (m=30000)

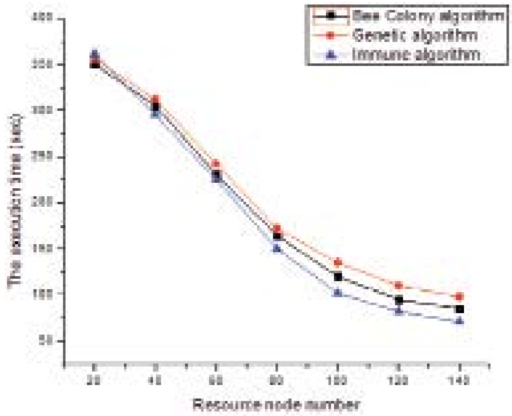

Figure 9. The execution time (sec) result of three algorithms (m=20000)

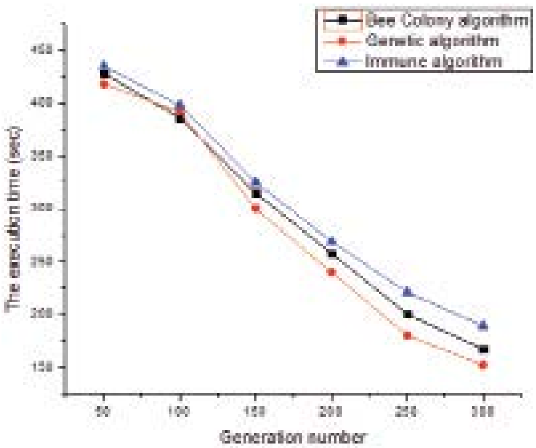

Figure 10. The execution time (sec) result of three algorithms (m=20000, n=100)

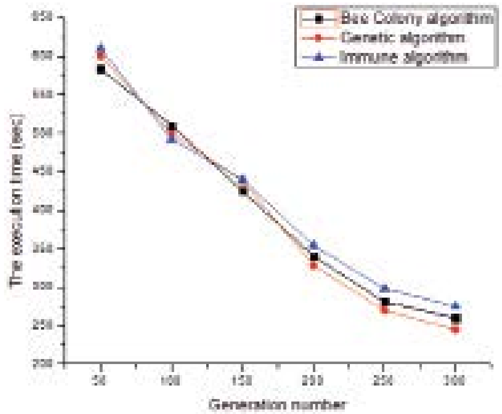

Figure 11. The execution time (sec) result of three algorithms (m=20000, n=150)

nodes n = 100, the average response time of Immune algorithm is less than Genetic algorithm by 1.86s, less than Bee Colony algorithm by 0.54s. When the resource nodes n = 120, the average response time of Immune algorithm is less than Genetic algorithm by 2.12s, less than Bee Colony algorithm by 0.68s. With the increasing number of tasks in grid computing system, the response time of Bee Colony algorithm and Genetic algorithm consumed increased by a big margin; Immune algorithm response time required rate of increase is relatively flat, suggesting that the algorithm can have certain scalability.

Fig. 6 shows the comparison result of the response time under different resource nodes (m = 30000). When the resource nodes n <= 40, performances of Immune algorithm, Bee Colony algorithm and Genetic algorithm are closer; When the resource nodes n <= 250, the performance of Immune algorithm algo-

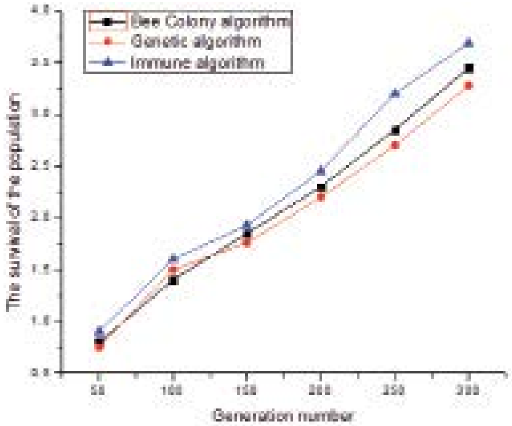

Figure 12. The survival of the population of three algorithms (m=30000, n=100)

rithm is better than other two algorithms. The average response time for Immune algorithm algorithm is less than Bee Colony Algorithm by 0.48s, and less than genetic algorithm by 0.72s.

Fig. 7 shows the comparison result of the response time under different resource nodes (m = 20000). When the resource nodes n <= 60, the performances of Immune algorithm algorithm and Genetic algorithm algorithm are relatively close, but the performance of Immune algorithm algorithm algorithm is relatively poor compared to Bee Colony algorithm. When the resource nodes n> 60, the performance of Immune algorithm algorithm is better than other two algorithms.The average response time for Immune algorithm algorithm is less than Bee Colony Algorithm by 0.28s, and less than Genetic algorithm algorithm by 0.34s, suggesting that Immune algorithm algorithm is more suitable for large-scale grid system.

Fig. 7 and 8 is the execution time comparing under different resource nodes. As the number of nodes in the grid system resources is increasing, three algorithms execution time was dramatically reduced. During the entire task scheduling, immune algorithm in most cases the performance is optimal; the relatively poor performance of Genetic algorithm, mainly because that Genetic algorithm is prone to premature convergence.

In Fig. 8, average execution time required for Immune algorithm is probably less than Bee Colony by 21.30%, less than the Genetic algorithm by 25.19%; Bee Colony algorithm and Genetic algorithm performance are relatively close; in Fig. 9, The average execution time needed by Immune algorithm is less than the Bee Colony algorithm about 12.47%, and 28.78% less than the Genetic algorithm.

In the execution time comparing of Fig. 10 and 11, execution time of Immune algorithm in most cases are minimal; Immune algorithm time consumption is about 82.10% of Bee Colony algorithm, while only about 65.84% of Genetic algorithm;

Early in evolution, the search performance of the three algorithms performance is very good; with the evolution of algebra increase the execution time sharply reduces; In the later stage of evolution, the performance curve performance of the three algorithms are relatively stable, reflecting the gradual evolution of depth, the algorithm gradually find the optimal solution.

In the same application environment, the highest population viability of the initial populations evolved after Immune algorithm, which obtained the best overall antibody performance. Among them, the survival of the population in Fig. 12 of Genetic algorithm is about 7100% of Immune algorithm; the population viability of the Bee Colony algorithm is about 94.25% of Immune algorithm of. In Fig. 12 population viability of the Genetic algorithm is about 776% of Immune algorithm; the population viability of Bee Colony algorithm is about 88.94% of Immune algorithm of.

Conclusion

As typical evolutionary algorithms, artificial immune lgorithm, Genetic algorithm and Bee Colony algorithm have their own advantages. This paper introduced the basic knowledge of evolutionary algorithms, and detailed respectively descriped the characteristics of three algorithms, including how to be proposed, features and algorithm steps. Then in this paper, meta task scheduling and intelligent optimization algorithms in grid resource scheduling were as test method, under different parameters conditions analyzed and compared the performance of three algorithms. At last the comparison result was given.

Conflict of interest

Authors declared that there is no conflict of interest.

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Research on Power Load Forecasting Models Based on Simulated Annealing Support Vector Machine (SA-SVM) Algorithm Mathematical

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