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An Improved Adaptive Genetic Algorithm based on Chaos Optimization

Jiale Zhang, Jiaxing Zhao, Shuangyu Duan and Lianshuan Shi*

School of Information Technology Engineering, Tianjin University of Technology and Education, Tianjin 300222, China

Abstract

Based on the current genetic algorithm in the premature convergence easily precocious phenomenon and problems such as parameter selection to rely too much on experience, proposed a improved adaptive genetic algorithm based on chaos optimization. This paper combines genetic algorithm with chaotic mapping, the use of the characteristics of both improve the performance of the algorithm. By introducing chaos mechanism in the algorithm, the use of the ergodicity of chaos, randomness and sensitivity to initial conditions, to optimize the genetic algorithm. The introduction of the adaptive mechanism at the same time, the algorithm of iterative process is optimized. Based on the genetic parameter adaptive adjustment, greatly improve the convergence precision of genetic algorithm, speed up the convergence. Finally, this paper uses several kinds of typical test functions, the algorithm was tested and the comparative analysis. The experimental results show that the improved hybrid algorithm can not only effectively avoid algorithm trapped in local optimum, and at the same time to improve the ability to function optimization, convergence speed and precision.

Keywords

Genetic Algorithm; Adaptive; Chaos; Optimization.

1. Algorithm Introduction

Genetic algorithm is an intelligent optimization algorithm simulated by researchers based on biological evolution in nature [1]. Combine the idea of "natural selection and survival of the fittest" with gene recombination and mutation in genetic theory [2]. Genetic algorithm does not limit the continuity and differentiability in the selection of objective function, and only needs a clear objective function value to calculate, so it has a very outstanding performance in solving nonlinear and non-normal problems. Genetic algorithm has good robustness and more comprehensive global search optimization ability, its adaptability, domain knowledge independence, parallelism, can better deal with large-scale complex data, and is especially suitable for solving multi-objective optimization problems, so it is widely used in daily research. Chaos is a seemingly irregular and random physical phenomenon existing in complex motion. At the initial stage, it seems to have only slight differences, but after a period of movement, their mutual relationship will gradually disappear [3]. Using the characteristics of chaos search can effectively help the algorithm to jump out of local optimal.

The basic process of genetic algorithm is to determine the appropriate coding mode according to the target characteristics, generate each chromosome, and merge these chromosomes into the initial population. Then, selection, crossover and mutation are used to screen the excellent chromosomes layer by layer and preserve them from generation to generation until the optimal solution of the target problem is obtained [4]. However, genetic algorithm also has its inherent defects, such as large amount of calculation, slow speed and other problems are also hot spots for research and improvement [5]. Chen Mingjie et al. [6] designed improved adaptive

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crossover and mutation probability and proposed an improved adaptive genetic algorithm based on population fitness concentration. Yuan Mengfei et al. [4] introduced adaptive crossover mutation operators into the algorithm and retained elite individuals genetically to better balance the local search and global optimization performance of the algorithm.

Chaos itself has the characteristics of "randomness", "ergodicity" and "regularity", and can traverse all states without repetition according to its own "regularity" in a certain range. Pan Wei et al. [3] proposed a kind of chaotic "micro-variation" genetic algorithm, which uses chaos characteristics to solve the premature problem that genetic algorithms are prone to fall into local optimal solutions. Ni Shaoquan et al. [5] introduced the elite selection coefficient in the process of offspring population renewal in order to improve the diversity of the population, and adjusted the probability of crossover mutation in the algorithm iteration process by combining the idea of self-adaptation. Liang Jingdong et al. [7] used clustering method of clustering degree to maintain the diversity and distribution of chromosome solutions while conducting chaotic search.

Since the characteristics of chaos help to overcome the genetic algorithm into local optimal, improve the search ability of the algorithm, the combination of the two is helpful to solve the objective function. In this paper, the algorithm is improved based on the above ideas. Firstly, the chaos mapping is combined with the genetic algorithm, and the ergodic range of chaos motion is "amplified" into the value range of the whole optimization variable. At the same time, the crossover mutation operator is improved, and the adaptive operator is introduced to balance the local search ability and global optimization ability of the algorithm, to dynamically adjust the population in the evolution, which is beneficial to prevent premature phenomenon and jump out of the local optimal.

2. Algorithm Optimization

2.1. Genetic Operator Optimization

2.1.1. Selection Operator

The excellent individuals in the population will be selected with a greater probability, the inferior individuals will be eliminated with a greater probability, so that the population towards a better direction, such an operation is called selection. At present, there are commonly used proportional selection, no replay random selection, sorting selection. Proportional selection is the most common roulette selection strategy in daily research. Individual fitness is proportional to the probability of being selected. No return random selection is based on the survival expectation of each individual in the next generation of random selection operation; The sorting selection method allocates the probability of each individual being selected by sorting individuals according to fitness [8].

The selection operator in this paper adopts roulette selection strategy. The main idea of roulette strategy is to determine whether individuals of a population will be selected into the new population and participate in the following crossover and mutation according to the proportion of individual fitness value to the total fitness value of the population. So that the survival of the fittest, to adjust the evolution of the population. The main steps of roulette selection are as follows:

(1) According to the fitness function, calculate the fitness value of each individual in the population;

(2) Calculate the total fitness value of the population, and calculate the probability of an individual's inheritance to the sub-population according to the proportion of the fitness value of the individual;

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(3) Calculate the cumulative probability of each individual according to the individual probability obtained in step 2;

(4) Random numbers r was generated within interval 0,1;

(5) When $r < q_1$, select individual 1, otherwise, individual k is selected, so that: $q_{[k-1]} < r \leq q_{[k]}$ holds;

(6) Repeat steps (4) and (5) above until termination conditions are met.

2.1.2. Crossover Mutation Operator

Crossover, also known as recombination, is an important part of genetic manipulation. New individuals are generated through crossover operation, in which the excellent genes of the previous generation of individuals are retained as much as possible, and the global search capability of the algorithm is improved [9]. Mutation is also an important part of genetic manipulation and is usually carried out after crossover operation. On the original basis of new individuals generated by crossover operators, population renewal can be carried out through mutation to increase population diversity and improve the local search ability of the algorithm, which can better prevent premature phenomenon [10]. The decision variables of the test function selected by the algorithm are relatively complex, so the encoding method in this paper adopts real number encoding [11].

Crossover operations are implemented by arithmetic crossover operators. Let two individuals x_i^m, $x_i^n (m \neq n)$ perform the arithmetic crossover at time i, then the two new individuals generated at time $i + 1$ after the crossover are:

$$x_{i+1}^m = x_i^m - \theta * (x_i^m - x_i^n) \tag{1}$$

$$x_{i+1}^n = x_i^n - \theta * (x_i^m - x_i^n) \tag{2}$$

In the above formula,θis a parameter. When it is set to constant, crossover operation is uniform algorithm crossover, while when it is variable, it is non-uniform arithmetic crossover.

The variation method is real number variation:

$$x_{i+1} = x_i - \varepsilon * rand \tag{3}$$

Same as the previous crossover formula,εis a parameter,randis corresponding to a random number between(0,1).

In crossover operation, the setting size of crossover probability will greatly affect the update result of the population. When the crossover probability is set too high, the good individuals will be destroyed easily. On the contrary, if the value is small, it cannot promote the evolution of the population, so that the population is difficult to effectively evolve. The same is true for mutation probability. Reasonable variation of population individuals can improve population diversity and avoid population falling into local optimum. However, once the mutation probability is set too high, the algorithm will be like random search, thus losing the characteristics of biological genetic evolution [12].

Based on the above theory, the value of crossover probability is discussed, and a new adaptive crossover probability formula is proposed. The adaptive efficiency of the algorithm can be improved by associating the evolutionary algebra with the fitness value. When our algebra increases, the population evolution becomes better and better, the crossover probability decreases correspondingly, and the mutation probability increases correspondingly to improve the local search ability of the algorithm. When the fitness value is smaller than the current algebraic average, we should reduce the crossover mutation probability; similarly, when the fitness value is larger than the current algebraic average, we should increase the crossover mutation probability [13]. Through the improvement of adaptive crossover variation, chromosomes can timely adjust their fitness values according to the changes in the current population fitness values, and dynamically adjust with the evolution process, which is conducive to avoiding premature population and jumping out of local optimum [7].

The adaptive crossover probability formula is as follows:

$$P_c = \begin{cases} 0.8 - 0.3 * \left(\frac{g}{G} + \frac{f_{avg} - f_s}{f_{max} - f_{min}}\right)\left(f_s \leq f_{avg}\right) \\ 0.8 - 0.6 * \frac{g}{G}\left(f_s > f_{avg}\right) \end{cases} \tag{4}$$

The adaptive mutation probability formula is as follows:

$$P_m = \begin{cases} 0.01 + 0.03 * \left(\frac{g}{G} - \frac{f_{avg} - f}{f_{max} - f_{min}}\right)\left(f \leq f_{avg}\right) \\ 0.01 + 0.09 * \frac{g}{G}\left(f > f_{avg}\right) \end{cases} \tag{5}$$

Among them:

f_sThe individuals with small fitness value in the crossed parent generation;

$f_{avg}$is the average of the population;

$f_{min}$is the minimum fitness value in the current population;

f is the fitness value of the current individual variation;

g is the current evolution algebra of the population;

G is the total number of iterations of the algorithm.

2.2. Chaos Optimization

Logistic mapping is a typical representative of chaotic mapping, which has a simple mathematical expression and is widely used in our research [6]. In this paper, it is applied to genetic algorithm to optimize the population and improve the optimization effect. Its mathematical expression is as follows:

$$X_{n+1} = X_n * \mu * (1 - X_n) \tag{6}$$

In the above formula,$\mu$is called Logistic parameter,$\mu \in [0,4]$.When $X \in [0,1]$,And at$\mu = 4$,the system is in complete chaos, the sequence generated under the action of Logistic mapping is aperiodic and non-convergent. When chaotic search is used, better results can be obtained than random search, so that the quality of individual population and computational efficiency can be improved.

After genetic operation, chaos optimization is carried out to the current optimal value of the population. After interval mapping, chaotic search is carried out for the current optimal individual. When a more excellent individual appears in the search process, any individual in the population is randomly replaced, and the optimal individual of the population is updated and then the iteration is continued. If no individual better than the current optimal value is found, the original optimal individual is still used to continue the iteration. When the termination condition is met, the search ends.

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2.3. Optimization Algorithm Flow

The main steps of the improved chaos optimization adaptive genetic algorithm are as follows:

Step 1: Population initialization uses a real number of encodings to produce N particles as the initial population;

Step 2: Select the appropriate test function and construct it as fitness function;

Step 3: Evaluate the fitness of the population, and select individuals to enter the algorithm for the next generation evolution according to the roulette selection strategy;

Step 4: According to the adaptive crossover mutation probability proposed in this paper, crossover mutation is carried out for the qualified individuals;

Step 5: Chaotic search is conducted on the optimal particle of the population. If the particle with better fitness value than the current is found, it is regarded as the optimal individual, and then an individual in the current population is randomly replaced.

Step 6: Judge whether the termination conditions of the algorithm are met. If the conditions are met, terminate the algorithm and output the results; otherwise, proceed with the above steps 3 to 5 and start a new round of iteration.

The algorithm flow chart is Shown in Fig.1:

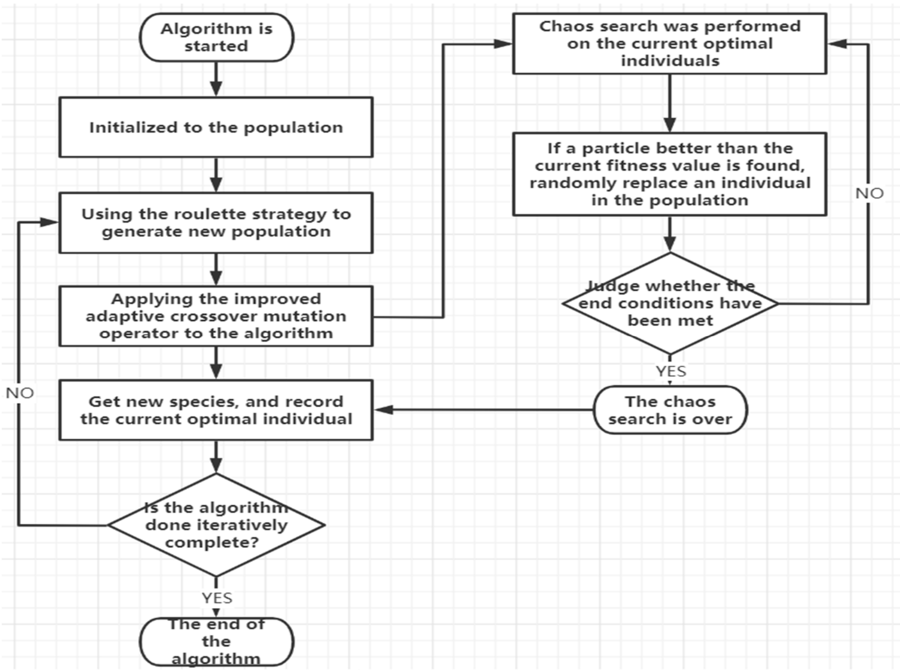


Fig 1. Algorithm flow chart

3. Experimental Analysis

3.1. Test Function

In order to better verify the feasibility and effectiveness of the proposed algorithm, four typical test functions are selected here. Including single-peak and multi-peak functions, test functions are as follows:

(1) The Griewank function, with the following formula:

$$f(x_i) = \sum_{i=1}^{N} \frac{x_i^2}{4000} - \prod_{i=1}^{N} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{7}$$

Among them, $X_i \in [-600,600]$, there are many local minima, the global minimum at $X = (0,0,\ldots,0)$, is a typical nonlinear multimodal function, Griewank function has many widely distributed local minima, these minima are regularly distributed, the function is often used to detect whether the algorithm is local or global convergence, Fig.2 is its function model.

(2) The Rastrigrin function, with the following formula:

$$f(x_i) = \sum_{i=1}^{D}[x_i^2 - 10\cos(2\pi x_i) + 10] \tag{8}$$

Among them, $X_i \in [-5.12,5.12]$,this function is a multipeak function, with a global minimum of 0 at $X = (0,0,\ldots,0)$, is also a nonlinear multimodal function, the position of the minimum is regularly distributed, Fig.3 is its function model.

(3) The Ackley function, with the following formula:

$$f(x_i) = -c_1\exp\left(-0.2\sqrt{(\frac{1}{n}\sum_{j=1}^{n}x_j^2)} - \exp(\frac{1}{n}\sum\nolimits_{j=1}^{n}\cos(2\pi x_j))\right) + c_1 + e \tag{9}$$

This function is an n-dimensional function with a minimum at $(0,0,\ldots,0)$, which is difficult to discern the optimal direction of the search, solve the global optimal difficulty, and is widely used to test the optimization algorithm. Fig.4 is its function model.

(4) The Sphere function, with the following formula:

$$f(x_i) = \sum_{i=1}^{D}x_i^2 \tag{10}$$

The Sphere function has D local minima, which are continuous, convex, and unimodal, and Fig.5 is for its function model.

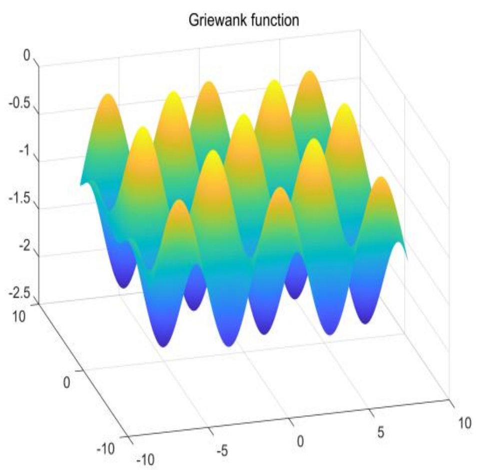


Fig 2. The Griewank function

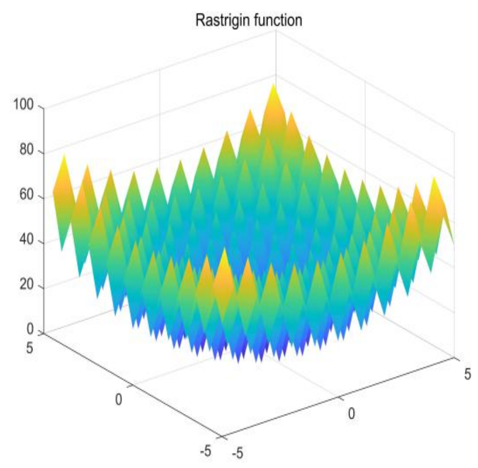
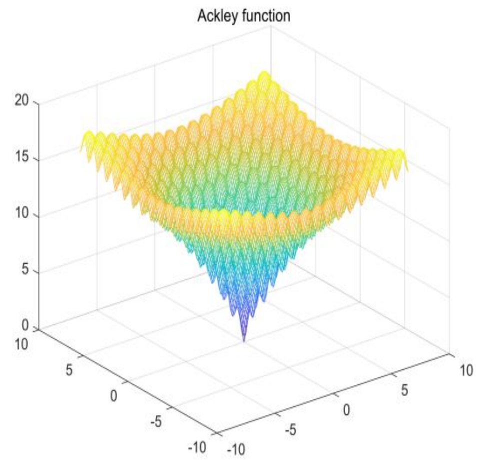


Fig 3. The Rastrigrin function



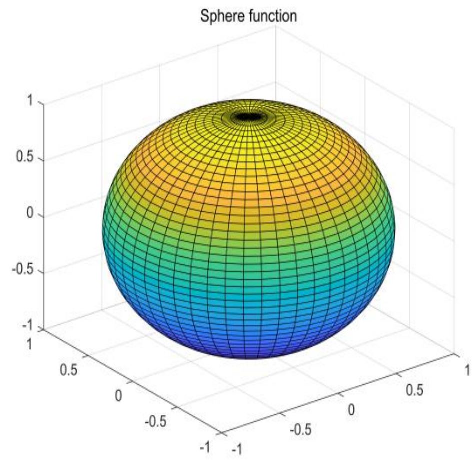


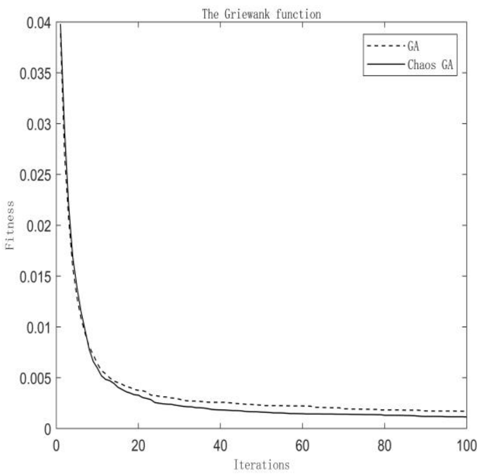
Fig 4. The Ackleyfunction **Fig 5.** The Sphere functions

3.2. Experimental Results

The specific parameters of the population in the algorithm are set as follows:

The initial population size N was 100, iterative algebra set G to 100 generations and particle dimension set to 5 dimensions.

The results of 100 experiments are selected to avoid randomness and ensure the validity and authenticity of the algorithm.Fig.6 to 9 show the evolutionary images of the Griewank, Rastrigrin, Ackley, and Sphere functions, respectively.



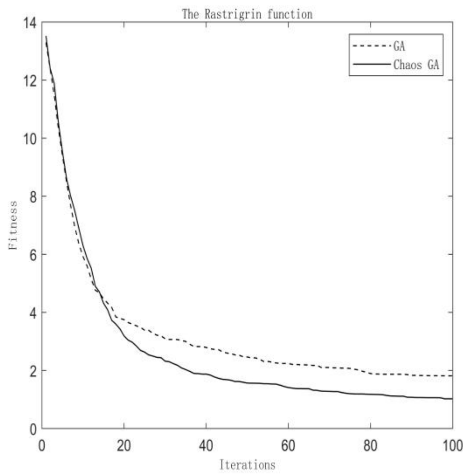
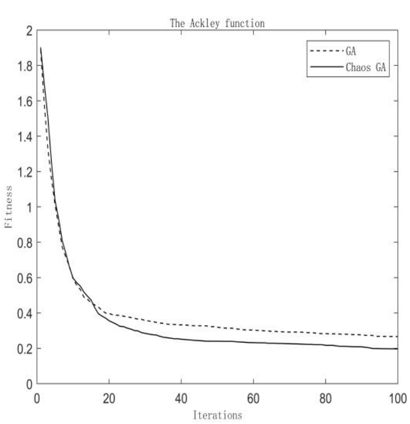


Fig 6. Griewank function contrast Fig **Fig 7.** Rastrigrin function contrast Fig



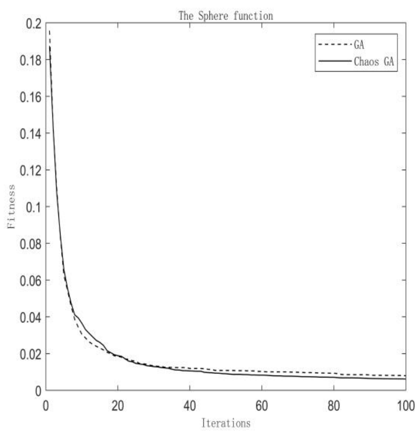


Fig 8. Ackley function contrast Fig **Fig 9.** Sphere function contrast Fig

As shown in the figure above, the improved algorithm is smoother on the function image, and it is more effective on finding the optimal value compared with the traditional genetic algorithm. Especially for the Rastrigrin function and the Ackley function, it is obvious in the image that after 100 experiments eliminate the randomness, the improved algorithm is better than the traditional algorithm in both optimization ability and convergence speed. At the same time, for Griewank function and Sphere function, although the two images are very close, but because the image is the average of 100 times of the results, so actually in the aspect of function optimization has been greatly improved, The comparison of the test function on the optimal value of the two algorithms can be seen in Table 1.

In general, through image comparison, it is not difficult to see that the improved chaos adaptive genetic algorithm has an obvious optimization effect on the population in the early stage compared with the original simple genetic algorithm. And with the iteration process, the improved optimization algorithm can find the optimal value earlier, and its optimization ability is greatly improved compared with the simple genetic algorithm, and the convergence accuracy and convergence speed of genetic algorithm are also greatly improved.

Table 1. Comparison of the algorithm's optimal values

Function	Simple genetic algorithm	Adaptive chaotic genetic algorithm
The Griewank function	4.84E-05	3.69E-05
The Rastrigrinfunction	4.2E-02	1.6E-02
The Ackleyfunction	4.95E-02	2.52E-02
The Spherefunction	4.77E-04	2.57E-05

The above table above shows the optimal values obtained by each test function in the two algorithms, among which the sphere function is the most obvious, rising from 4.77E-04 to 2.57E-05, and the other functions are also greatly improved. from the above image and table analysis, it can be seen that the improved chaotic adaptive genetic algorithm effectively avoids the local optimal algorithm, and also greatly improves the optimization ability and convergence speed. The improved algorithm proposed in this paper is effective.

4. Conclusion

After the overall performance of genetic algorithm and chaos optimization has been greatly improved. Using the characteristics of chaos, the adaptive mechanism is introduced into the algorithm to greatly improve the algorithm. The experimental results show that the optimized algorithm quickly finds the optimal value, and the optimization ability is greatly improved compared with the simple genetic algorithm, and the convergence accuracy speed of the genetic algorithm is also greatly improved. Due to the limitation of experimental conditions, there are some defects in function selection and parameter setting, and we will continue to study and improve them in the future.

References

[1] Chai Yan, Zhou Yanzhao. Mountain-climbing method improvement of the genetic algorithm [J]. Journal of Liaoning University of Engineering and Technology (Natural Science edition), 2014,33 (07): 996-999.

[2] Fan Linan, Lu Peng. Campus takeout delivery path planning based on an improved genetic algorithm [J]. Logistics Technology, 2021,44(01):14-19. DOI:10.13714/j.cnki.1002-3100.2021.01.004.

[3] Pan Wei, Ding Lichao, Huang Feng, Sun Yang. Based on the chaotic "microvariation" adaptive genetic algorithm [J]. Control and Decision Making, 2021,36(08): 2042-2048.DOI:10.13195/j.kzyjc. 2021. 0319.

[4] Yuan Mengfei, Kan Xiu, Cao Le, Wang Jialin, Wu Jianzhen, Luo Xiao. Express delivery vehicle path planning [J]. Journal of Navigation and Positioning, 2021,9(06): 104-111.DOI:10.16547/j.cnki.10-1096. 20210616.

[5] Ni Shaoquan, Luo Xuan, Xiao Bin. Considering the interests of the three parties [J / OL]. Journal of Southwest Jiaotong University: 1-10 [2022-04-07]. http:// kns.cnki. net/kcms/ detail/ 51.1277. U.20220330.1618.022.html.

[6] Chen Mingjie, Liu Sheng. Application of improved adaptive genetic algorithms in function optimization [J]. Journal of Harbin Engineering University, 2007 (08): 875-879.

[7] Liang Jingdong, Guo Jianjun, Liang Haihong, Guo Fengyi. Multi-objective genetic algorithm based on chaotic local search [J]. Journal of Liaoning University of Engineering and Technology (Natural Science edition), 2010,29 (04): 630-633.

[8] Wu Weiyong, Lotte. Review of selection operators in genetic algorithms [J]. Fujian Computer, 2012, 28 (06): 43-44.

[9] Deng Chunyan. Cross-operator analysis of the genetic algorithm [J]. Agricultural Network Information, 2009 (05): 124-126.

[10] Shen Chang, Lotte. Review of the variation operators in genetic algorithms [J]. Technology Vision, 2012 (23):107-108+188. DOI:10.19694/j.cnki.issn2095-2457.2012.23.043.

[11] Jin Juliang, Yang Xiaohua, Ding Jing. Accelerated genetic algorithm based on real-number encoding [J]. Journal of Sichuan University (Engineering Science Edition), 2000(04):20-24. DOI: 10. 15961/ j. jsuese. 2000. 04.006.

[12] Wang Ruiqi, Zhang Chenghui, Li Ke. Multi-objective genetic algorithm based on improved chaos optimization [J]. Control and Decision Making, 2011,26(09): 1391-1397.DOI:10.13195/j.cd. 2011. 09. 114. wangrq.025.

[13] Xiong Siying, Dong Lijun. Adaptive genetic algorithm for labeled plane stereographs [J]. Journal of graph, 2018,39 (06): 1105-1111.