# Optimization of nonlinear functions based on improved genetic algorithm

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#### **ABSTRACT**

Premature convergence and falling into local optimum easily are important problems for genetic algorithm. Therefore a new algorithm is constructed in this paper, which can be performed among multiple populations by introducing different optimization parameters. The final formation is aggregated into an elite population, where genetic operations such as selection, crossover, mutation, etc. do not exist, for the purpose of ensuring that the optimal individuals selected between different populations are not destroyed and lost. The simulation results show that the algorithm used in this paper has better optimization ability and higher calculation accuracy for solving local optimal problems of nonlinear functions.

Keywords: Function optimization, multi-population, immigration operator, efficiency

#### 1. INTRODUCTION

Many problems, such as engineering design, combinatorial optimization, decision-making, optimal path selection, etc., can be reduced to function optimization problems after mathematical modelling<sup>1</sup>. Finally, the optimal results can be solved under certain constraints, which can reduce manpower expenditure. Therefore, it is meaningful to discuss the problem of function optimization in theory and application.

Genetic Algorithm (GA) is first proposed by John Holland in the 1970s in the United States<sup>2</sup>. Genetic algorithm comes from the natural evolution process of nature. The algorithm solves the optimal solution through mathematical coding, and uses the selection, crossover and mutation process to search for the optimal result. Because the optimization is independent of gradients and has strong robustness and global search ability, combinatorial optimization problems can be quickly and accurately solved. GA had been widely used in combinatorial optimization, machine learning, signal processing, adaptive control and other fields<sup>3</sup>.

However, many of its deficiencies and defects have also been exposed, such as poor local search ability, slow convergence speed and it is easy to fall into local optima<sup>4</sup>. With the expansion of the dimensions of the problem to be optimized, these deficiencies are becoming more and more prominent, and the most prominent problem is the problem of premature convergence. All individuals in the group tend to the same state and stop evolving, the biodiversity is lost, and it is meaningless to iterate again.

A multi-population genetic algorithm (MPGA) can be used to replace the conventional standard genetic algorithm. Multi-population genetic algorithm performs among multiple populations by introducing different optimization parameters, and the optimization results are derived from the final elite population. Compared with the traditional GA, the improved MPGA has better adaptability and result accuracy for solving the multimodal function optimization problem with high difficulty coefficient<sup>5</sup>.

This paper proposes to use the new algorithm to solve the overall optimization problem of multimodal nonlinear functions, and changes the relevant variables to observe the stability of the algorithm and compared it with the traditional genetic algorithm. Simulation results show that the MPGA has better optimization ability and higher calculation accuracy for solving local optimal problems of nonlinear multimodal functions.

#### 2. DISADVANTAGES OF GENETIC ALGORITHMS

Genetic algorithm is a random search algorithm. The first step is to randomly generate a population, then searches for the optimal solution of the optimization problem through genetic operations to generate a new population. After gradual

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evolution, the GA converges to the optimization accurately with a high probability, so as to obtain the optimal solution or sub-optimal solution of the optimization problem<sup>6</sup>. The GA structure is shown in Figure 1.

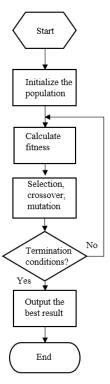


Figure 1. GA flow chart.

Premature convergence problem is one of the biggest problems of GA<sup>7</sup>. All individuals in the group tend to the same state and stop evolving, the biodiversity is lost, and it is meaningless to iterate again.

The occurrence of premature convergence is mainly related to the following aspects<sup>8</sup>:

- The selection operation is carried out according to the probability determined by the fitness value of the individual. When there is an individual abnormal individual in the group (the individual's fitness is much higher than other individuals). Under the action, the next generation group will soon be controlled by this one, which will cause the group to stagnate.
- The frequency of crossover and mutation operations is controlled by the probability of crossover and mutation. Optimization results are heavily influenced by the values of the crossover probability and mutation probability. Different values are likely to lead to different calculation results.
- The size of the population also affects the optimization results. When the size of the group is small, the degree of diversity in the group is low, and the competition among individuals is weak. Relying on mutation operations to maintain, the population will soon terminate the evolution; when the value of the population size is large, it will inevitably cause an increase in the amount of calculation, and the calculation efficiency will be affected.
- In the case that the user's goal is not fully achieved, the program judges that the optimization has reached the optimal solution, and ends the optimization cycle.

#### 3. MULTI-POPULATION GENETIC ALGORITHM

#### 3.1 Algorithm improvement

Based on the original standard GA, MPGA mainly introduces the following concepts<sup>9</sup>:

- Breaking through the framework of the standard genetic algorithm that only relies on a single population for genetic evolution, which can be performed among multiple populations by introducing different optimization parameters.
- The various populations are connected through the migration operator. The optimal solution is obtained through the co-evolution of multiple populations.
- The optimal individuals in each evolutionary generation of each group are preserved and selected to decide whether to achieve optimal convergence.

The structural flow chart of the MPGA is shown in Figure 2.

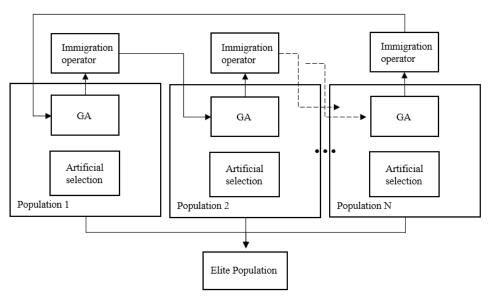


Figure 2. Schematic diagram of the structure of MPGA.

In this paper, binary coding is used for individuals, which has high stability and large population diversity. The decision variables  $x_1$  and  $x_2$  are represented by binary strings. For example, the domain of  $x_j$  is  $[a_j, b_j]$ , and the accuracy requirement is ten thousandths, which requires the domain of  $x_j$  to be divided at least $(b_j - a_j) \times 10^5$  spaces, and the binary string length required by the set variable  $x_i$  is  $m_j$ , which should satisfy:

$$2^{m_j-1} < \left(b_j - a_j\right) \times 10^5 < 2^{m_j} - 1$$

### 3.2 Immigration operator

Through a certain probability, the selection operator selects excellent individuals from the current population to form a new population, so that the excellent individuals can reproduce in the offspring<sup>10</sup>. In the multi-swarm genetic algorithm, various groups are independent of each other. The immigration operator is a medium for the exchange of information among various groups, and it introduces the optimal individuals that appear in the evolution of each group into other groups.

# 3.3 Elite population

The elite population is the re-selected population and the basis for judging termination. In each generation of evolution, the best individuals from other populations are selected and stored in the elite population<sup>11</sup>. The formed elite population does not carry out genetic operations to ensure that the optimal individuals generated by each population are not destroyed and lost during the evolution process.

#### 4. EXPERIMENTAL DESIGN AND RESULTS

This paper selected the following typical nonlinear multimodal functions for research and analysis

$$f(x,y) = x\sin(2\pi y) + y\sin(2\pi x)$$

We set a small area for calculation. The value range of x in f(x, y) is [-2,2], and the value range of y is [-2,2]. Through the initial derivation, it is concluded that the stagnation point range is not within the definition domain, and the optimal value of the function should be obtained at the boundary. Near (0,0), the function will oscillate, and it is easy to generate local extrema.

In order to test and evaluate the performance of MPGA for multimodal function optimization, this paper defines the optimal solution value, iterative stability, and optimal time as the algorithm evaluation indicators.

This paper compares the standard GA and the improved MPGA. Table 1 shows the initial setting of the genetic algorithm and the influence on the results after considering the changes of the crossover probability and mutation probability.

GA	Crossover probability	Mutation probability	Number of individuals	Genetic algebra	Generation gap
1	0.7	0.05	40	500	0.9
2	0.8	0.05	40	500	0.9
3	0.7	0.02	40	500	0.9

Table 1. Initial parameters and variables of GA.

The variation of the optimal solution of the GA with the evolution number is shown in Figure 3.

Table 2 shows the parameter settings of the improved multi-population genetic algorithm. Since the immigration operator between multiple populations can communicate with each population, the crossover probability and mutation probability will take a random probability between each population.

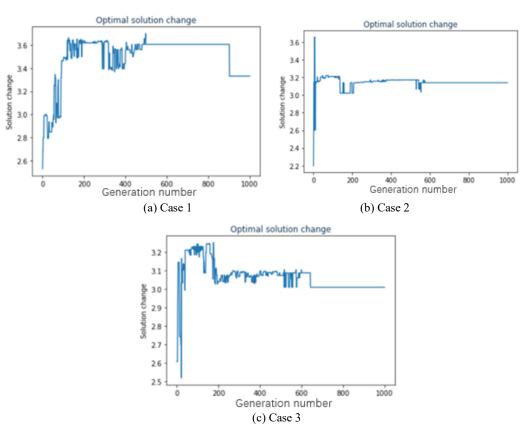


Figure 3. Optimal solution change.

Table 2. Improved initial parameters of MPGA.

MPGA	Crossover probability	Mutation probability	Number of individuals	Genetic algebra	Generation gap
/		[0.001,0.05] Random number	40	10	0.9

Table 3 shows the calculation results. The standard genetic algorithm was calculated 7 times. Due to the existence of crossover and mutation probability, the results are different each time. However, the improved genetic algorithm can better obtain a stable optimal value.

The variation of the optimal solution of the GA and the MPGA with the evolution number is shown in Figure 4.

The optimization results obtained each time are different by using genetic algorithm, (as shown in Table 3 above), and even the signs of x and y are opposite. It could be seen that the standard genetic algorithm is very unstable, and sometimes it is still not stable when it is close to 500 generations, the convergence speed is slow, and the convergence accuracy is poor.

Using the improved multi-population genetic algorithm, the optimization results obtained each time are completely consistent, the stability is good, the genetic algebra is within 30 generations, the convergence speed is fast, and the convergence accuracy is high, which is suitable for the optimization of such complex functions.

Table 3. GA and MPGA algorithm optimization results.

GA	X value	Y value	Optimal solution	Optimal time (evolutionary algebra)
1	1.7894	-1.9879	3.7116	258
2	-1.7395	1.5212	3.2421	130
3	-1.7539	1.5351	3.2461	153
4	-1.7255	1.5086	3.2136	106
5	1.7856	-1.9823	3.7075	398
6	-1.7657	-1.4907	3.2462	263
7	1.7576	-1.9855	3.7335	437
MGPA	X value	Y value	Optimal solution	Optimal time (evolutionary algebra)
1	1.7627	-2	3.7563	15
2	1.7627	-2	3.7563	10
3	1.7627	-2	3.7563	9
4	1.7627	-2	3.7563	13
5	1.7627	-2	3.7563	9
6	1.7627	-2	3.7563	16
7	1.7627	-2	3.7563	13

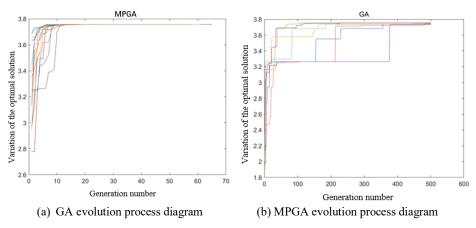


Figure 4. Evolution process diagram.

## 5. CONCLUSION

The improved MPGA expands the structure of the standard GA, and introduces multiple populations to search the solution space at the same time, and greatly reduces the inappropriate genetic control parameters. The influence of the settings on the optimization results has a significant effect on suppressing the occurrence of immature convergence. The examples show that the multi-population genetic algorithm has better optimization ability and higher calculation accuracy and stability for solving the local optimal problem of nonlinear multimodal functions.

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