Environmental Governance and Protection Financing Scheme Based on a Dimensional Multi-Objective Genetic Algorithm

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ABSTRACT: *This article proposes an environmental governance and protection financing scheme based on a low-dimensional multi-objective genetic algorithm to solve the problem of insufficient funding for environmental governance and protection projects. This plan effectively utilises funds, improves investment returns, and reduces risks by optimizing portfolio investments. This article first introduces the background and significance of environmental governance and protection financing, then elaborates on applying a low dimensional multi-objective genetic algorithm in optimizing portfolio investment. Finally, the feasibility and effectiveness of this scheme are verified through experiments. The experimental results indicate that the environmental governance and protection financing scheme based on a low dimensional multi-objective genetic algorithm can effectively solve the financing problem of environmental governance and protection projects and has important theoretical significance and practical application value.*

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1. Introduction

In managing investment and financing projects for environmental protection and environmental pollution control, the returns and risks of investors are affected by various uncertainties. Suppose the investor does not have professional expertise in environmental protection and pollution control, investing only in speculation or preference. In that case, investment failure will affect personal funds and social development [1]. Establishing an investment portfolio model with high efficiency and good effect and scientifically solving it will inevitably provide a more reliable basis for decision-making on investment and financing of environmental pollution control and environmental protection [2]. It can effectively improve the success rate of environmental pollution and environmental protection projects, which play an important role in ensuring environmental protection and green development [3]. The main goal of the portfolio model is to reduce investment risk and increase profitability. The method adopted is to optimize the investment and placement of funds. As the current popular investment theory, the current research has moved from symbolic qualitative research to quantitative research supported by mathematical models [4]. With the rise of artificial intelligence machine algorithms, using intelligent algorithms to solve the portfolio model greatly improves the efficiency and accuracy of the operation. Starting from the characteristics of nonlinear constraints of investment and financing, heuristic algorithms such as genetic algorithm, simulated annealing algorithm, and tabu search intelligent algorithm all play a unique role in the solution of the portfolio model [5]. Starting from the characteristics of using funds for environmental pollution control and environmental protection, according to the current requirements for double-objective investment, a genetic algorithm is introduced to optimize the solution to the portfolio model. With good algorithm accuracy and quality, we can ensure that environmental protection investment and financing achieve the goal of reducing risk and increasing revenue [6].

2. State of the Art

During the nearly sixty years since the birth of the Genetic Algorithm (GA), it has entered many industries and fields closely related to human social life and work [7]. A critical watershed in the study of genetic algorithm theory is the emergence of a modern genetic algorithm with adaptive characteristics that can handle complex computational conditions well. When searching for space, the genetic algorithm is not limited, and it can cover all feasible solution spaces for initial point selection. Such an operation effectively avoids the situation that the optimal value result only represents a certain locality [8]. The introduction of genetic factors also has a good effect on global search, which makes the newly generated generation structure always keep the best condition. A genetic algorithm is a kind of intelligent artificial algorithm embodying the laws of nature that "the survival of the fittest is dispelled and discomfort is eliminated". It is the wisdom of human society's continuous evolution. The algorithm's theoretical basis is using mathematical models to simulate the process of biological evolution [9]. The genetic algorithm brings the process of choosing the optimal solution into natural evolution. The sample population is used as the problem representative, and the genetic factors bring the sample to the population. After the operations such as selection, crossover, and mutation, a new population generation is obtained. Multiple iterations of reciprocal search training will be conducted to ensure the optimality of the population, and the individual with the greatest fitness will be selected as the optimal solution. The genetic algorithm uses multiple iterations to find new approximate solutions based on the individual's fitness values generated in different problem domains, using continuous selection, crossover, and optimization processes. This truly simulates the entire process of population evolution in the natural environment, This allows the resulting new individual to demonstrate better adaptability to the environment than in the past [10]. Genetic factors can play a role in continuously improving the optimization of population collections. They can keep good structures to the next generation or produce better structures.

3. Methodology

3.1. Genetic Algorithm

The most important feature of genetic algorithms is their ability to adapt to environmental laws, which is very similar to the changing environmental conditions in investment and financing. The greatest advantage of genetic algorithm is that it can perform global parallel search efficiently. During the search process, the model will actively acquire and accumulate various types of knowledge in the search space, and adaptively control the search process to achieve the best solution. The genetic algorithm uses multiple iterations to find new approximate solutions based on the individual's fitness values generated in different problem domains, using continuous selection, crossover, and optimization processes. This truly simulates the entire process of population evolution in the natural environment. This allows new individuals to adapt better to the environment than past individuals. Genetic factors can play a role in continuously improving and optimizing population combinations. They can keep good structures for the next generation or produce better structures. Genetic factors can respond to changes promptly, effectively reducing possible local optimization problems in the search for best-mode solutions. In the initial population selection, the genetic algorithm will randomly select the initial population of the object at the beginning and choose the value between 20 and 100. In the constrained optimization problem, the initial population must be based on diversity, randomness, and homogeneity to ensure the feasibility of individual populations. It is challenging to achieve the goal of randomly selecting populations under this requirement. In the case of multiple dimensions and many constraints, using only a random algorithm will increase the initial population selection time and directly affect the efficiency of the genetic algorithm. Therefore, two researches on the initial population are carried out. The first step is to use the internal correction method to generate the initial point based on the initial population in the feasible region. The second is introducing mathematical principles and using scientific search methods to find an internal point that cannot give an initial point artificially.

The genetic algorithm requires the search of the initial population for the combination of data sets. Figure 2 illustrates the principle of implementing individual search in the initial population. Here $\chi_1^{(1)}$ is the internal point of the feasible region, which is the initial point to be taken. After the initial population looks for the first individual χ_1, it randomly generates subsequent individuals $\chi_2 = [\chi_1, \chi_1, \cdots, \chi_n]$. If χ_2 is a viable individual, it continues to transmit the next individual. If χ_2 is not a feasible individual, adjust it according to $\chi_2 \Leftarrow \chi_1 + \alpha(\chi_1 + \chi_2)$. At $\alpha = 0.5$, you can get the position of the new point between χ_1 and χ_2. Afterwards, all the points in the initial population needed can be found similarly.

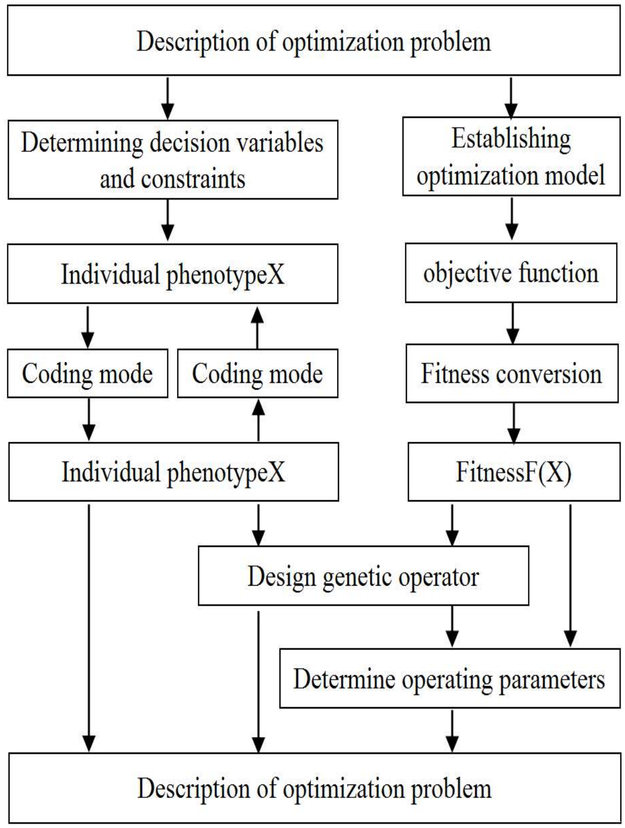

Figure 1. Schematic diagram of genetic algorithm design process

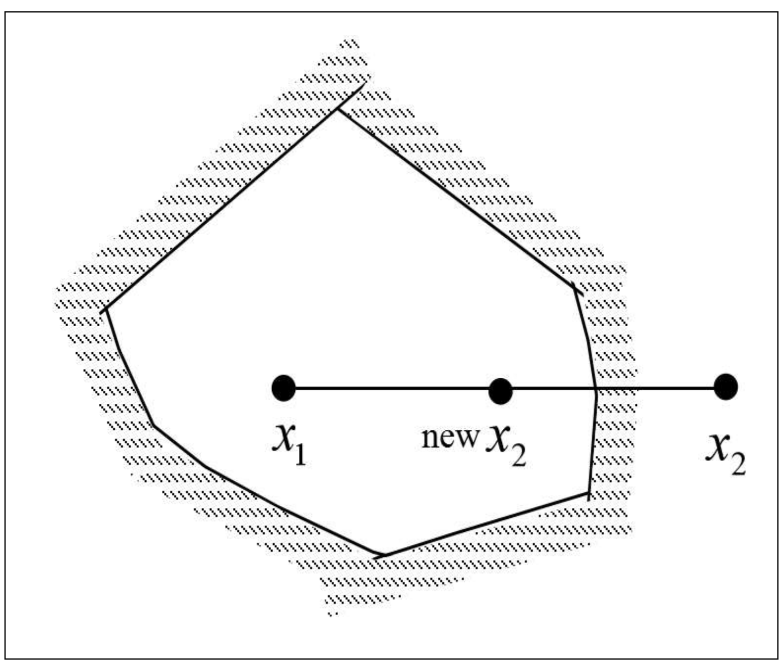

Figure 2. The principle of searching for individuals of initial population in genetic algorithm

In each iteration of the genetic algorithm model, better individuals will enter the new population generation. You need to design a selection strategy to determine which effective individuals are entering the next generation. The selection probability is used to achieve the selection process of excellent populations. The mathematical principle is to calculate the individual fitness of the population separately and calculate the sum to find the proportion of the individual in the population. If the computed proportion is high, these effective individuals are more likely to be selected into new populations than others. Let the fitness value of individual i in group M be denoted by f_1. The selection probability equation for excellent individuals can be calculated using formula (1):

$$P_i = \frac{f_i}{\sum_{i=1}^{M} f_i} \tag{1}$$

The calculation process is to calculate the individual fitness values f_1, $i = 1, 2,..., M$ for the individual population first. Then, use formula (2) to solve the fitness of all individuals in the entire population and calculate the sum of fitness.

$$F = \sum_{i=1}^{M} f_i \tag{2}$$

The probability of the individual's choice is calculated using the formula (3). The above steps are the wheel method. The selection process is the process of selecting M rotations. To avoid the ageing of the population, fresh individuals are also added each time during the rotation to increase the vitality of the population. Set the pseudo-random number r to be evenly distributed between zero and one. The first individual is selected; otherwise, the k-th individual ($2 \leq k \leq M$) is selected, and the setting is established. In this way, M selections are made, and genetic operators are derived. In the design of genetic operators, multiple experiments are required to finally set the reasonable range and size of genetic algorithm parameters. This article uses roulette. The principle of roulette selection is shown in Figure 3.

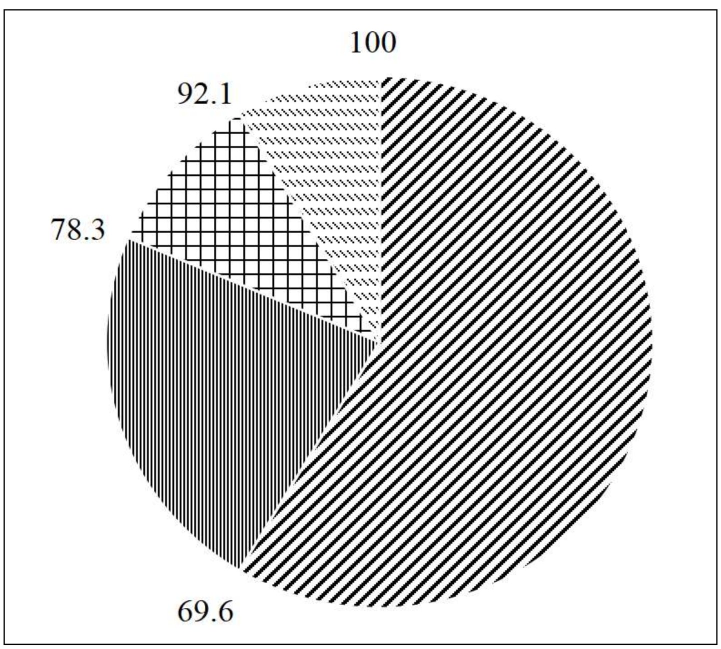

Figure 3. The principle of roulette selection based on genetic operator

3.2. Solving Strategy of Portfolio Selection Model based on Genetic Algorithm

Although genetic algorithms have the advantage that other algorithms do not have, there are inherent deficiencies in the algorithm. Genetic algorithm adopts a fixed method of strategy parameters, and the search results are not good. There is no way to solve the problem of changes and dynamics of the strategy parameters in genetic evolution. The prominent performance is that the crossover and mutation probability cannot be controlled. Therefore, the basic genetic algorithm can not objectively reflect the different changes in the population at different stages of evolution. After analyzing the principles, advantages and disadvantages of the basic genetic algorithm, it is found that the performance of the genetic algorithm is greatly affected by the parameters. If the parameters are fixed, then how to ensure that the choice is appropriate is a major issue. If the parameters are not properly selected, genetic algorithms may also have different conclusions for different problems.

$$p_c = \begin{cases} p_{c\_\max} - \left(\dfrac{p_{c\_\max} - p_{c\_\min}}{it\max} \right) * iter & f^1 \geq f_{avg} \\ p_{c\_\max} & f^1 < f_{avg} \end{cases} \tag{3}$$

$$p_c = \begin{cases} p_{c\_\min} + \left(\dfrac{p_{m\_\max} - p_{m\_\min}}{it\max} \right) * iter & f^1 \geq f_{avg} \\ p_{c\_\min} & f^1 < f_{avg} \end{cases} \tag{4}$$

To make crossover probability and mutation probability adaptive to dynamic conditions, the calculation of fitness value is introduced and a genetic algorithm flow based on the dynamic adjustment of crossover and mutation probability is built. The adjustment formula is shown in formulas (3) and (4). The crossover probability in the formula is denoted by p_c where p_{c_max} represents the maximum crossing probability, p_{c_min} represents the minimum crossing probability, p_m represents the maximum variation probability, p_{m_max} represents the maximum variation

probability, and p_{c_min} represents the minimum variation probability. *it max* represents the largest evolutionary algebra, *iter* represents the current evolutionary algebra, f_{avg} represents the average fitness value of the population, f^1 represents the individual with greater fitness in the two individuals to be cross-operated, and f represents the fitness of the individual who needs to perform the mutation operation. After the optimized genetic algorithm, p_c and p_m can automatically change with the fitness value, p_c but when the individual fitness value is close or equal to the maximum fitness value, p_c and p_m will be close to or equal to zero. Suppose the algorithm is in the early stages of evolution. In that case, it will appear that the good individuals are almost in a state of immutability, which causes the whole algorithm to look for a local optimal solution. Therefore, the algorithm continues to be optimized.

$$p_c = \begin{cases} p_{c1} - \dfrac{(p_{c1} - p_{c2})(f^1 - f_{avg})}{f_{\max} - f_{avg}} & f^1 \geq f_{avg} \\ p_{c1} & f^1 < f_{avg} \end{cases} \tag{5}$$

$$p_m = \begin{cases} p_{m1} - \dfrac{(p_{m1} - p_{m2})(f^1 - f_{avg})}{f_{\max} - f_{avg}} & f^1 \geq f_{avg} \\ p_{m1} & f^1 < f_{avg} \end{cases} \tag{6}$$

Adapt the fitness formula to equations (5) and (6). Where f_{max} represents the maximum individual fitness value in the population and f_{avg} represents the average fitness value. f_1 represents the individual with greater fitness in the two individuals to be cross-operated, and set $p_{c1} = 0.9$, $p_{c2} = 0.6$, $p_{m1} = 0.1$, $p_{m2} = 0.01$. In this way, the crossover probability and the mutation probability of the individuals with the greatest fitness in the population do not show a zero value, so that the excellent individuals can be in a state of constant change, which can help the genetic algorithm to achieve a global search to select the optimal solution.

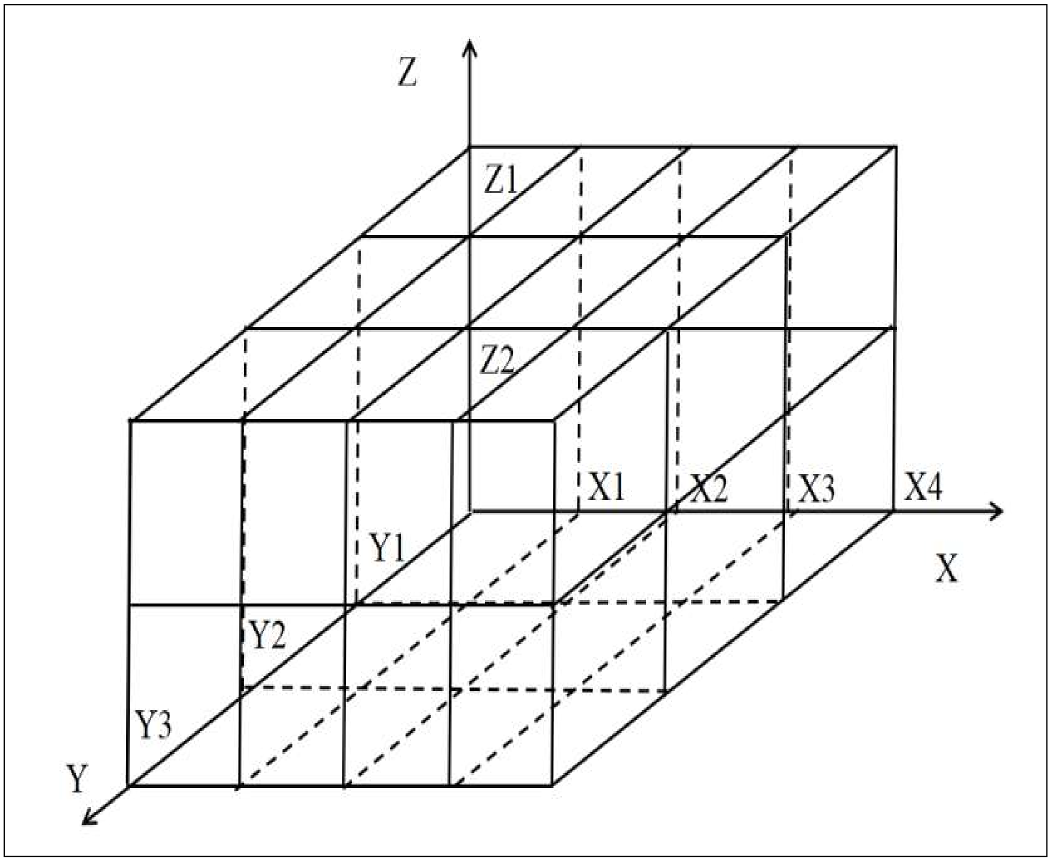

Figure 4. Three dimensional structure of alleles

In order to reduce the complexity of decoding when genetic algorithm is used to encode data structures, three-dimensional data structure is used to show the alleles of the algorithm to help analyze the nature of the data as soon as possible. This operation makes the investment and financing information intuitive and visual, and the fitness calculation procedure will not be too complicated. The three-dimensional array of alleles is shown in Figure 4. It uses cube coordinates to represent three-dimensional arrays. The X axis is the time axis, and each interval corresponds to a time interval. The Y axis and Z axis represent related parameter information that affects the data.

In the computational solution to the constrained optimization problem, the convergence speed and performance of the genetic algorithm are greatly affected by the initial population. Therefore, optimizing and improving the initial population is an important factor in improving the accuracy of the genetic algorithm. In general, for the unconstrained optimization problem, the initial population can meet the needs of the algorithm as long as it satisfies the uniform distribution, randomness, and diversity. However, in the constrained optimization problem, the initial population must be based on diversity, randomness, and homogeneity to ensure the feasibility of individual populations. It is difficult to achieve the goal of randomly selecting populations under such requirements. In the case of multiple dimensions and many constraints, applying only the random algorithm will extend the initial population selection time and directly affect the efficiency of the genetic algorithm. Therefore, two researches on the initial population are carried out. One is to use the internal correction method to generate the initial population based on feasible points. The second is to use a scientific search to find an internal point where humans cannot give an initial point. The optimized genetic algorithm implementation process is shown in Figure 5.

4. Result Analysis and Discussion

In order to verify the performance of the genetic algorithm for the portfolio model of the paper, the investment and financing data of environmental pollution and environmental protection projects in M province from 2010 to 2017 are used for simulation

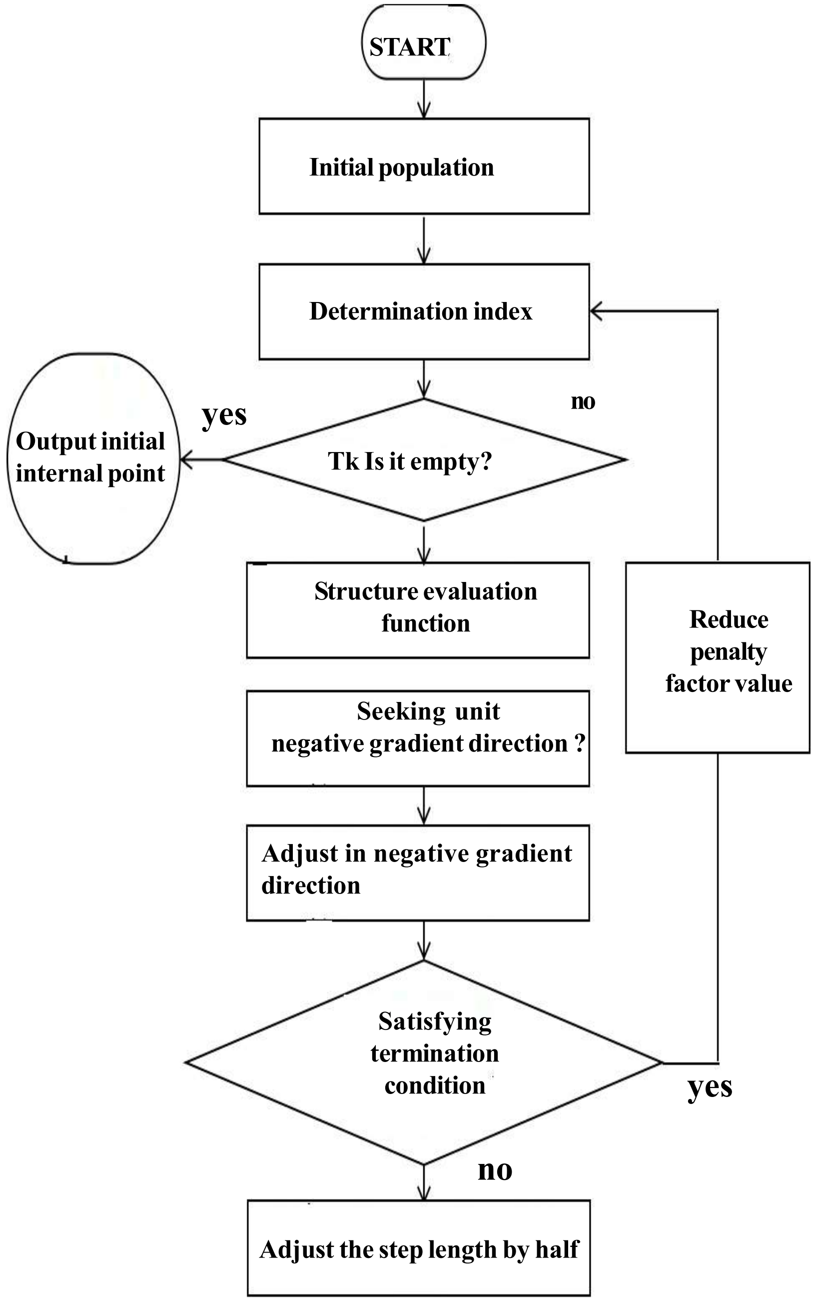

Figure 5. Method of generating initial population

experiments. The experiment first sets the ideal parameters, and generates simulated investment and financing sample data according to this ideal set of parameters. Then, the genetic algorithm is used to optimize the sample data and compared with the preset ideal parameters to test the effectiveness of the algorithm proposed. The number of experimental population is 90, the number of parameters is 25, the length of cell string is 6, the mutation probability is 0.3, the crossover probability is 0.2, the weight is 0.4, and the sample size is 160000. The partial data generated by the experiment is shown in Table 1.

Then compare the situation of the search task completion time for the collection of fund data for environmental pollution and environmental protection investment and financing projects. A set of data sets is set up that contain 10 sets of data {100, 200, 300, 400, 500, 600, 700, 800, 900, 1000}. In the simulation test, we compare the empirical design, ant colony algorithm and the

Generation	Evaluation error of optimal solution and ideal value	Evaluation variance of optimal solution and ideal value
0	0.232801	0.294211
60	0.021616	0.073457
100	0.033783	0.037679
160	0.014716	0.017932
200	0.008323	0.0116489

Table 1. Optimal Solution Error

optimized genetic algorithm. The same conditions are used for basic data and computer system configurations. Under this condition, the comparison of this algorithm test is obtained. Figure 6 shows the data collection task execution time comparison chart. The abscissa here is the number of task sets, and the vertical coordinate represents the completion time of the task. As can be seen from the figure, the optimized genetic algorithm will increase time steadily when the number of early tasks is small. Even if the task size increases and the environmental conditions become more and more complex, the optimization algorithm model can quickly search for the global optimal solution. Therefore, it can be seen that the optimized genetic algorithm has a great advantage in the completion time of the optimal mode search.

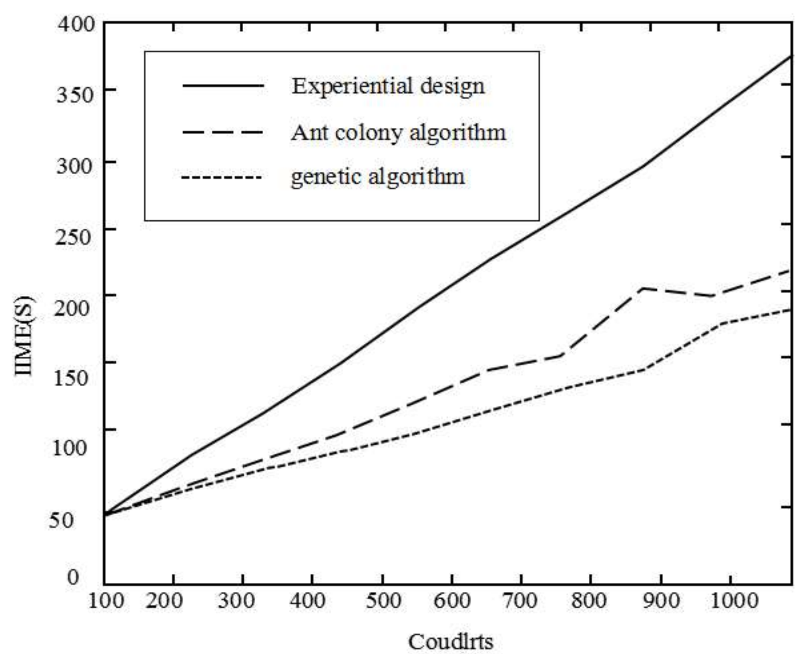

Figure 6. Small data task execution time contrast diagram

The genetic algorithm performs a random mode in operation. When the algorithm converges, finding the best individuals is mainly obtained by adaptive stochastic calculations. The maximum number of iterations of the simulation algorithm is set to 260 times in order to calculate the optimal number of experiments for a single individual. Figure 7 shows the result of the optimized genetic algorithm over one hundred iterations. As can be seen from the figure, the above line represents the development of the individual. The following line represents the development trend of the adaptation of all individuals in the population. The trend of the individual’s optimal adaptability in the graph is relatively flat. At the end of the population convergence, the rise will stagnate. The appraisal adaptability of the entire group is not under very stable development.

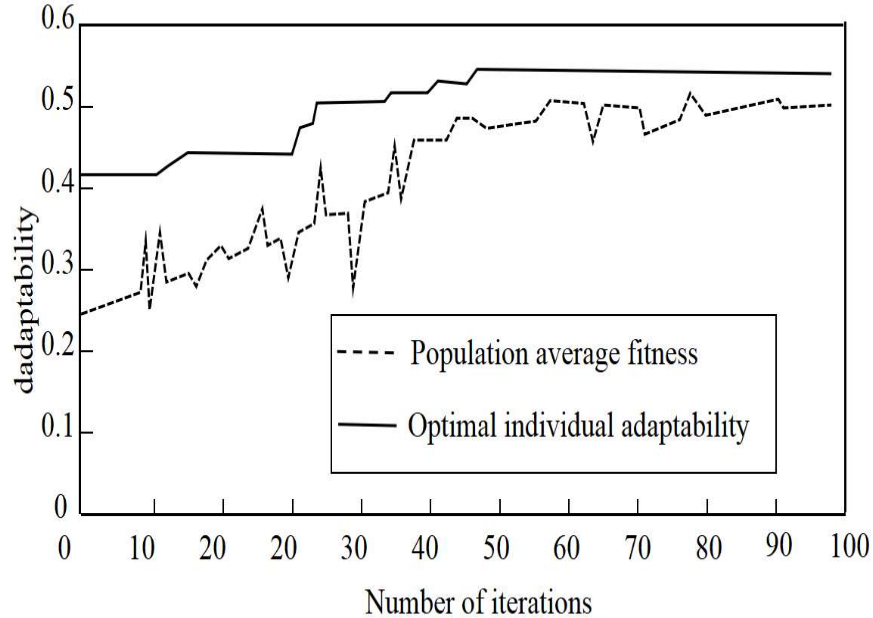

Figure 7. Results of optimal genetic algorithm at 100 iterations

5. Conclusion

The genetic algorithm learns the best strategies for human evolution and biological inheritance. Through the establishment of artificial intelligence mathematical model, it is applied to fields such as data mining, image processing, business management, and optimization combination. The solution of portfolio model based on genetic algorithm is studied. Mainly by optimizing the multi-objective problems that affect environmental pollution and environmental protection, the genetic algorithm’s operational efficiency advantages in solving optimization problems are reflected. Based on the analysis of the basic principle of the genetic algorithm and the mathematics solving process, the self-adaptation formula of the crossover probability and the mutation probability under the dynamic index is proposed. According to the needs of the research of integrated teaching mode, allele coding of data structure is explored and updated. Finally, computer-assisted technology is used to test the algorithm. From the verification results, the solution to the portfolio model based on the genetic algorithm has better operating efficiency than other algorithms. This shows that the research on the predictive analysis model based on the genetic algorithm is successful. Of course, the test results also show room for improvement in the optimization of the genetic algorithm, and further improvement of the precision of the model is the future research direction.

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