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Dynamic Dissection of Improved Genetic Optimization Algorithm in Intelligent Innovation of Financial Performance Evaluation Indicators

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Abstract At present, there are many shortcomings of genetic optimization algorithm, including the complexity of genetic algorithm programming, involving gene coding and decoding, the setting of crossover rate, the mutation rate and other parameters in the algorithm determined by experience and the intense dependence on the merits of the initial population. In the financial performance evaluation, genetic optimization algorithm needs to artificially add and modify the evaluation indicators, and the new indicators can not increase the evaluation according to the situation, resulting in a large gap between the evaluation indicators. The data produced in the financial performance evaluation of enterprises is not accurate enough to achieve the optimal financial performance. On the basis of genetic algorithm, simulated anneal algorithm and machine learning technology were made up of a hybrid genetic optimization algorithm, which improved the population diversity of genetic algorithm, the intelligent data learning ability of genetic optimization algorithm and the efficiency of algorithm data decomposition and processing. After data comparison and analysis, it was finally determined that the improved hybrid genetic optimization algorithm was more accurate and intelligent in data analysis than the traditional genetic optimization algorithm, and the financial performance was also the best. For example, the highest rate of return of the improved algorithm in investment projects was 80%, and the highest accuracy of data analysis in the optimized financial performance system was 95%, which showed the effectiveness of the hybrid genetic optimization algorithm. The improved hybrid genetic optimization algorithm could indeed make the financial performance evaluation indicators more intelligent and efficient in the enterprise financial performance evaluation system and achieve better results in the field of financial performance evaluation.

Index Terms Genetic Optimization Algorithm, Financial Performance, Evaluation Indicator, Simulated Annealing

I. Introduction

With the development of science and technology, the popularization of computer science and technology has gradually faced all sectors of society. On the basis of computer technology, a variety of computer algorithms have been developed. At present, the five classic algorithms widely used in the computer field include divide and conquer, dynamic programming, greedy algorithm, back tracking method and branch and boundmethod. Genetic optimization algorithm is a genetic algorithm based on classical algorithm, while genetic algorithm belongs to random global optimization algorithm. With the maturity of computer technology, genetic optimization algorithms also play an important role in different fields.

As an improved algorithm of genetic algorithm, genetic optimization algorithm belongs to the same class of algorithms as genetic algorithm. If there is a need of understand genetic optimization algorithm, it is necessary to have a certain cognitive understanding of genetic algorithm. In the field of genetic algorithm, Dharma Faisal used the regression model of genetic algorithm to predict Indonesia's inflation rate, and explained the regression model of genetic algorithm in detail in his paper. He believed that the regression model of genetic algorithm could effectively analyze and construct inflation data and improve the accuracy of inflation data analysis [1]. Sun Yanan exerted genetic algorithms to automatically design cellular neural network (CNN) architecture for image classification. In his design, he clearly and carefully explained the types and algorithm theories of genetic algorithms and made more in-depth use of genetic algorithms [2]. Chen XiangLiu optimized and improved the genetic algorithm, combined machine learning technology with genetic algorithm and made practical use of the algorithm. Through genetic optimization algorithm, the ranking of courses in the course scheduling system became more intelligent, and the course arrangement was more scientific and reasonable [3]. N .Shanmugasundaram used genetic algorithm in road network design and vehicle driving distance optimization. He analyzed the driving road through the functional rationality and consistency of genetic algorithm and optimized the distance between vehicles in the process of driving by using the characteristics of small amount of calculation and strong universality of the algorithm, aiming to ensure the driving safety of automobile drivers [4]. Through the above literature, the relevant theoretical knowledge of genetic algorithm can be roughly understood. Summarizing the literature, it can be found that genetic algorithm, as a computer algorithm, is widely used in many fields, and its development space is large.

Although genetic algorithm is widely used, it is relatively limited by the current level of scientific and technological development. Genetic algorithm still has corresponding defects in many aspects, which also hinder the development of genetic algorithm. In order to improve the shortcomings of genetic algorithm, many scholars try to improve and optimize genetic algorithm. Abualighah Laith applied genetic optimization algorithm to the task scheduling problem of cloud computing. He reckoned that the combination of genetic optimization algorithm and hybrid multinode optimizer could also improve the problem of difficult and chaotic task scheduling to a certain extent [5]. Bi Kexin utilized adaptive cloud model and hybrid genetic algorithm to build and analyze the data of the new naphtha molecular reconstruction process. In terms of hybrid genetic algorithm, he also used the combination of particle swarm optimization algorithm and genetic algorithm and added adaptive cloud model technology to build a new hybrid genetic algorithm [6]. Ye Fei has carried out in-depth research on genetic algorithms. He proposed the evolution of support vector machine model based on hybrid methods, combining population optimization technology with genetic algorithms for medical diagnosis. He believed that genetic algorithms have certain defects and can not be applied to medical diagnosis and tried to use population optimization technology to improve genetic algorithms, hoping to promote the evolution of support vector machine model through hybrid methods [7]. Li Ning used genetic optimization algorithm in the research of ship collision avoidance path optimization. He added particle swarm optimization algorithm to the genetic algorithm, completed the analysis of a large number of ship collision avoidance path data through the optimization algorithm and found the optimal solution of collision avoidance path [8]. Through the review of the above literature, it is known that genetic algorithm does have many shortcomings, and it is also noted that the optimization of genetic algorithm has not been proposed and concerned only in recent years. At present, genetic optimization algorithm is widely used in many fields, and there are many kinds of optimization methods of genetic algorithm. According to the information consulted, the combination of genetic algorithm and particle set algorithm is more optimization methods at present.

Combined with the theory of genetic algorithm in the literature, considering the problem of expanding the development space of genetic algorithm and the application of genetic algorithm in real life, this paper decides to apply genetic algorithm to the financial performance evaluation of enterprises. By optimizing genetic algorithm, the problem of inaccurate data produced by traditional genetic algorithm in the financial performance evaluation of enterprises is improved, making the financial performance evaluation indicators more intelligent and efficient and achieving better results in the field of financial performance evaluation.

II. Theoretical System of Genetic Optimization Algorithm

As an optimization branch of genetic algorithm, the purpose of genetic optimization algorithm is to break through the limitations of traditional genetic algorithm, so that genetic algorithm can adapt to more fields and improve the efficiency and ability of genetic algorithm [9], [10]. Genetic algorithm was first proposed by American scholars in the 1970s. Genetic algorithm is a science and technology simulated by summarizing the laws of biological evolution in nature. It is a computational model of biological evolution process simulating the natural selection and genetic mechanism of Darwin’s biological evolution theory. It is a method to search for the optimal solution by simulating the natural evolution process [11], [12]. Genetic optimization algorithm is a method to search for the optimal solution by simulating the natural evolution process. For an optimization problem, the algorithm makes the population evolve to a better solution by performing selection, crossover, mutation, evaluation and other operations through a certain number of candidate solution population iterations. This paper attempts to combine genetic optimization algorithm with machine learning and simulated anneal algorithm to construct a hybrid algorithm based on genetic optimization algorithm. The algorithm not only includes the basic characteristics of genetic algorithm, but also covers the efficient autonomy of machine learning and the advantages of simulated anneal algorithm which is simple, general and robust, suitable for parallel processing. The hybrid algorithm can be used to solve complex nonlinear optimization problems. The following is the improved block diagram of genetic optimization algorithm, as shown in Figure 1:

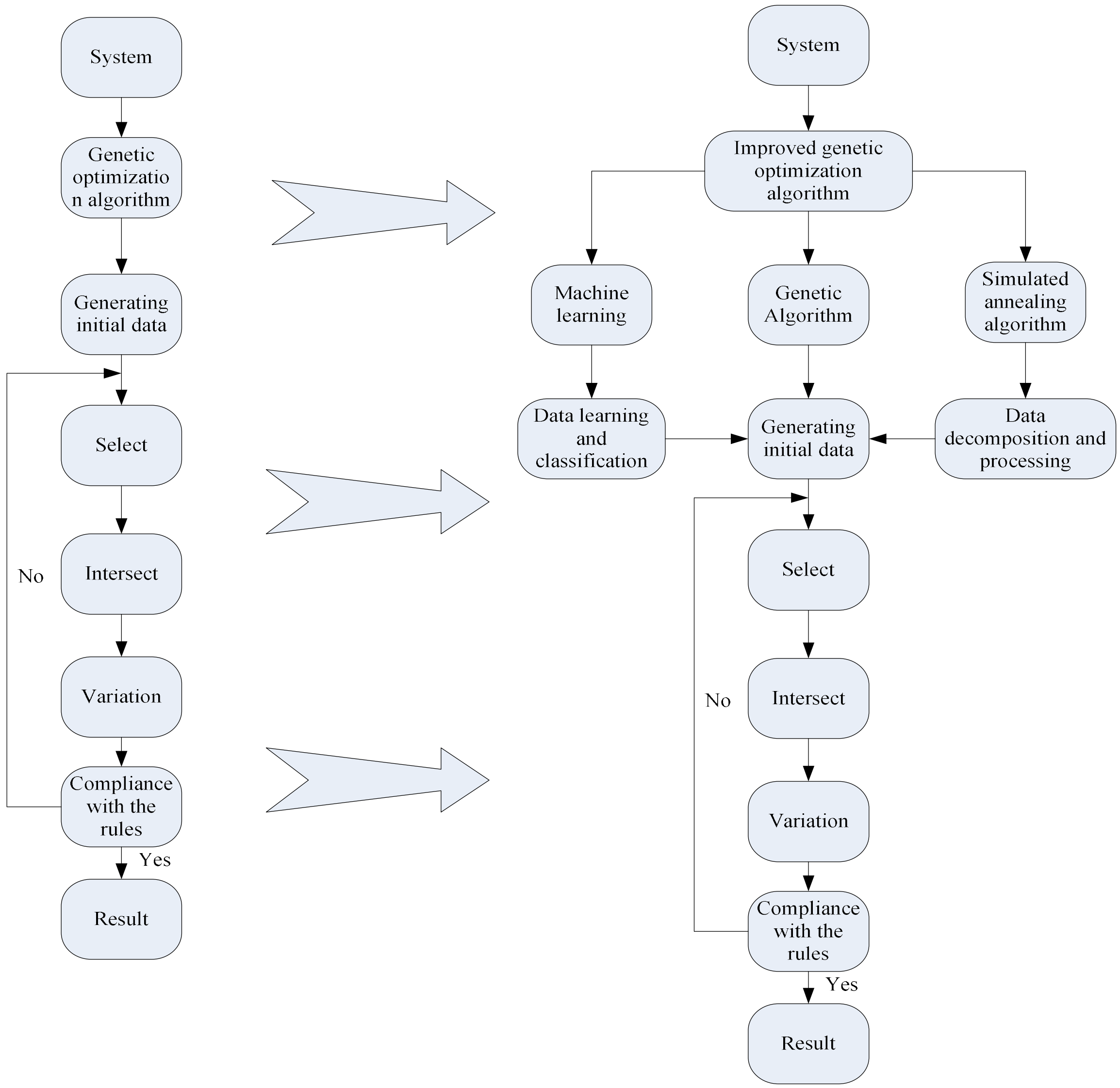

Figure 1: Block diagram of genetic algorithm improvement

II. A. Genetic Algorithm Theory and Method

The core of genetic optimization algorithm is genetic algorithm, which is a general algorithm to solve search problems, and can be used for all kinds of general problems. Genetic algorithm is evolved by simulating the biological evolution of nature, and its main operation idea is natural selection and the survival of the fittest. The overall search strategy and optimization search method of genetic algorithm do not need to rely on other auxiliary information. Only the objective function and the corresponding fitness function can be used for the overall search, so the genetic algorithm can automatically generate a very complex framework for solving complex systems when searching, and the corresponding data can be searched through this framework [13]. However, the advantage of using this framework is that this framework belongs to a general framework, which does not depend on the specific field of the problem and has very strong robustness to the type of problem, which greatly improves the ability of the framework to search data, so genetic algorithm is used in many fields. Among the characteristics of genetic algorithm, the selection of fitness function plays a very important role in genetic algorithm. Generally speaking, genetic algorithm automatically transforms the problem into a reasonable fitness function, uses the good and bad criteria to screen the data individuals in the function and filters out the inferior data, thus achieving the purpose of approaching the optimal value. Common fitness functions are mainly divided into the following types of functions, namely, direct conversion function, boundary construction function and conservative estimation function. The function formula of direct conversion method is as follows:

$$\mathrm{Fit}\big(\mathrm{E}(\mathrm{a})\big) = \mathrm{E}(\mathrm{a}) \tag{1}$$

$$\mathrm{Fit}(\mathrm{E}(\mathrm{a})) = -\mathrm{E}(\mathrm{a}) \tag{2}$$

Among them, Formula (1) represents the maximum value problem of the objective function; Formula (2) represents the minimum value problem of the objective function; $\mathrm{E}(\mathrm{a})$ represents the objective function to be solved; $\mathrm{Fit}(\mathrm{E}(\mathrm{a}))$ represents the fitness function converted from the objective function. The function formula of boundary construction method is as follows:

$$\mathrm{Fit}(\mathrm{E}(\mathrm{a})) = \begin{cases} \mathrm{B}_{\max} - \mathrm{E}(\mathrm{a}), \mathrm{E}(\mathrm{a}) < \mathrm{B}_{\max} \\ 0, \text{else} \end{cases} \tag{3}$$

$$\mathrm{Fit}(\mathrm{E}(\mathrm{a})) = \begin{cases} \mathrm{E}(\mathrm{a}) - \mathrm{B}_{\min}, \mathrm{E}(\mathrm{a}) > \mathrm{B}_{\max} \\ 0, \text{else} \end{cases} \tag{4}$$

Among them, $\mathrm{B}_{\max}$ represents the maximum estimate of $\mathrm{E}(\mathrm{a})$ and $\mathrm{B}_{\min}$ represents the minimum estimate of $\mathrm{E}(\mathrm{a})$. The function formula of conservative estimation method is as follows:

$$\mathrm{Fit}(\mathrm{E}(\mathrm{a})) = \frac{1}{1+\mathrm{B}-\mathrm{E}(\mathrm{a})}, \mathrm{B} \geq 0, \mathrm{B} - \mathrm{E}(\mathrm{a}) \geq 0 \tag{5}$$

$$\mathrm{Fit}(\mathrm{E}(\mathrm{a})) = \frac{1}{1+\mathrm{B}+\mathrm{E}(\mathrm{a})}, \mathrm{B} \geq 0, \mathrm{B} + \mathrm{E}(\mathrm{a}) \geq 0 \tag{6}$$

Among them, B is a conservative estimate of the objective function. In genetic algorithm, three different functions are used alternately to complete the processing and calculation of data, so as to achieve the purpose of obtaining the optimal solution of data.

II. B.Machine Learning Technology Theory

Machine learning is a multidisciplinary interdisciplinary specialty, covering probability theory knowledge, statistics knowledge, approximate theory knowledge and complex algorithm knowledge. It uses computers as tools, devotes to simulate human learning in real time and divides the existing content into knowledge structures to effectively improve learning efficiency [14]. In the field of machine learning, machine learning technology takes different ways to model practical problems according to different data types. Generally speaking, machine learning includes supervised learning, semi supervised learning and unsupervised learning, but the commonly used way is only supervised learning. Machine learning technology can not only intelligently learn data, but also innovate data according to existing data under certain circumstances to generate related new data types. The following is the dual formula of support vector machine using Lagrange function to derive optimization problem data:

$$\max \quad \mathrm{G} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{a}_{\mathrm{i}} - \frac{1}{2}\left(\sum_{\mathrm{i,k}=1}^{\mathrm{m}} \mathrm{a}_{\mathrm{i}}\mathrm{a}_{\mathrm{k}}\mathrm{b}_{\mathrm{i}}\mathrm{b}_{\mathrm{k}}\mathrm{c}_{\mathrm{i}}^{\mathrm{T}}\mathrm{c}_{\mathrm{k}}\right) \tag{7}$$

$$\text{subject to} \quad \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{b}_{\mathrm{i}}\mathrm{a}_{\mathrm{i}} = 0, \mathrm{a}_{\mathrm{i}} \geq 0 \quad \mathrm{i} = 1, \ldots, \mathrm{m} \tag{8}$$

Among them, Lagrange coefficient a_{i} is the solution of the optimization problem; c represents the vector of sample data; c_{i} represents the input sample data; b_{i} represents the correct classification label. Through the above formula, the input data can be basically learned and analyzed, assisting the genetic algorithm in computing.

II. C.Simulated Anneal Algorithm Theory

In the improved genetic optimization algorithm, in addition to genetic algorithm and machine learning technology, simulated anneal algorithm is added to optimize the genetic algorithm. The core idea of the algorithm mainly comes from the cooling process of physical solids. It needs to follow the Metropolis acceptance criteria, under which data can accept a disadvantage solution with a certain probability. With the continuous decline of temperature, the probability of receiving the inferior solution also decreases. When the temperature coefficient is 0, the probability of the inferior solution is 0. Through the acceptance criteria of simulated anneal algorithm, the algorithm can fall into the state of local optimal solution. Its mathematical expression formula is as follows:

$$\rho(\Delta\mathrm{F}, \mathrm{R}) = \begin{cases} 1 & \Delta\mathrm{F} \leq 0 \\ \mathrm{e}^{-\Delta\mathrm{F}/\mathrm{R}} & \Delta\mathrm{F} > 0 \end{cases} \tag{9}$$

Among them, ρ represents the acceptance probability of the new solution; $\Delta\mathrm{F}$ represents the difference between the value of the current solution and the previous solution; R represents the temperature parameter. The above formula is the core formula of simulated anneal algorithm, which plays an important role in the program of simulated anneal algorithm and is an important part of the program of simulated anneal algorithm. Its algorithm program can assist genetic algorithm in data decomposition and processing and improve the efficiency of genetic algorithm in data processing. Through the coordinated operation of the above three algorithms, an optimal hybrid algorithm based on genetic algorithm is finally formed, which is mainly based on genetic algorithm. The algorithm program is imported into the corresponding financial performance evaluation index system to process the financial performance data. The following is a partial interface operation diagram of the improved genetic optimization algorithm financial performance evaluation indicators system, as shown in Figure 2:

Figure 2: Partial interface operation diagram of genetic optimization algorithm financial performance evaluation indicators system

III. Performance Test of Improved Genetic Optimization Algorithm

III. A. Improved Genetic Optimization Algorithm Test

Compared with the original genetic optimization algorithm, the improved hybrid genetic optimization algorithm increases machine learning technology and simulated anneal algorithm, so its performance should also be improved. The role of machine learning technology in genetic optimization algorithm is to learn and analyze data, while the role of simulated anneal algorithm in genetic optimization algorithm is to decompose and process data. Whether the performance of the improved hybrid genetic optimization algorithm can be improved depends on the effectiveness of these two functional technologies, so it is necessary to test the performance of these two functions to ensure the successful operation of the hybrid technology. The following is the test data sheet for testing individual technologies. Machine learning technology test data sheet is shown in Table 1, and simulated anneal algorithm test data sheet is shown in Table 2:

Table 1: Machine learning technology test data sheet

Unit(%)	Test 1	Test 2	Test 3	Test 4
Data 1	90%	100%	97%	100%
Data 2	95%	100%	98%	100%
Data 3	100%	100%	99%	100%
Total	285%	300%	294%	300%
Mean	95%	100%	98%	100%

Table 2: Test data of simulated anneal algorithm

Unit(%)	Test 1		Test 2	
	Decomposition rate	processing rate	Decomposition rate	processing rate
Data 1	100%	100%	0%	0%
Data 2	100%	100%	100%	100%
Data 3	100%	100%	100%	100%
Total	300%	300%	200%	200%
Mean	100%	100%	66.67%	66.67%

The role of machine learning technology in genetic optimization algorithm is to learn and analyze data, so the test data of machine learning technology in Table 1 are the data recognition learning rate of machine learning technology. Considering that some data in machine learning technology may not be able to recognize learning, the recognition learning rate standard of machine learning technology was set at more than 90% in this paper. When the recognition learning rate reached more than 90%, the recognition learning ability of machine learning technology on data in genetic optimization algorithm did not have an increased impact on the system. Through the data in the table, it can be seen that in the three groups of data tested for four times, all the data have reached the recognition learning rate standard of more than 90%, among which in the second and fourth tests, all the data have reached 100% recognition learning rate, which showed that machine learning technology performed well in the application. Nevertheless, it is worth noting that in data 1 of the test 1, the test results showed that the recognition learning rate of this set of data was 90%, which just met the test standard. Combined with other data, the data gap in this group was large, and the reasons needed to be discussed and analyzed. After a comprehensive investigation and discussion, it was finally believed that the data components in this group were more complex, and some data were more remote and rare, so there were some difficulties in recognition learning, resulting in low results.

In the test of simulated anneal algorithm, the main function of simulated anneal algorithm is to assist genetic algorithm in data decomposition and processing, aiming to improve the efficiency of data processing. In other words, when the simulated anneal algorithm could not decompose the data, the data was transferred to the genetic algorithm for processing, which could lead to the genetic algorithm to spend a lot of computing power on data processing and seriously affect the speed of data processing. Through the data in the test data table of simulated anneal algorithm, it can be seen that in the test 1, the decomposition rate and processing rate of the three groups of data were 100%, which showed that in the test 1, all data have been decomposed by simulated anneal algorithm. However, in the test 2, there were obvious anomalies in the data 1, where both the decomposition rate and the processing rate were 0%. Combined with the fact that there were no problems in the data 2 and data 3, it was considered that there were more likely problems in the data 1, and then the test data were investigated. It was found that all the data 1 were special symbols, not conventional digital data. After investigation, it was found that, this data had corresponding digital data, which was convenient to convert all of them into special symbols for substitution, so the simulated anneal algorithm failed to decompose the data. After the problem was improved, the data were tested again, and the results showed that the data results after replacement were 100%, indicating that there was no technical problem in the application of simulated anneal algorithm.

III. B. Comparison of Actual Application Effect Data

Genetic optimization algorithm has absolute advantages over manual data processing, which is clearly described and analyzed in Li Xinyu's "an effective hybrid genetic algorithm and variable neighborhood search for integrated process planning and scheduling in a packaging machine workshop" [15]. However, for the improved genetic optimization algorithm, the ordinary genetic optimization algorithm is dwarfed. The following is a comparative analysis chart of performance data between traditional genetic optimization algorithm (hereinafter referred to as traditional algorithm) and improved hybrid genetic optimization algorithm (hereinafter referred to as improved algorithm) in practical application. The comparative analysis chart of return on investment data is shown in Figure 3, and the analysis chart of operating profit margin data against score is shown in Figure 4:

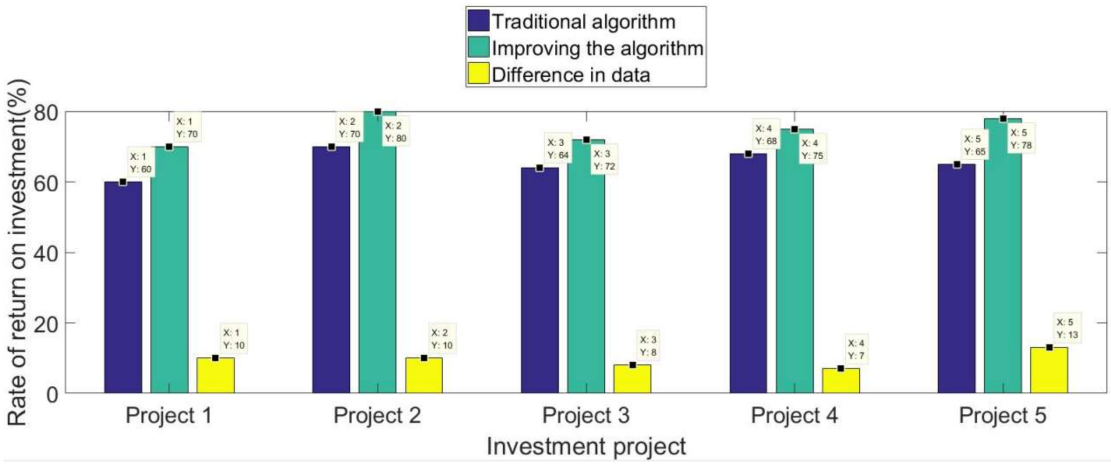

Figure 3: Comparative analysis of return on investment data

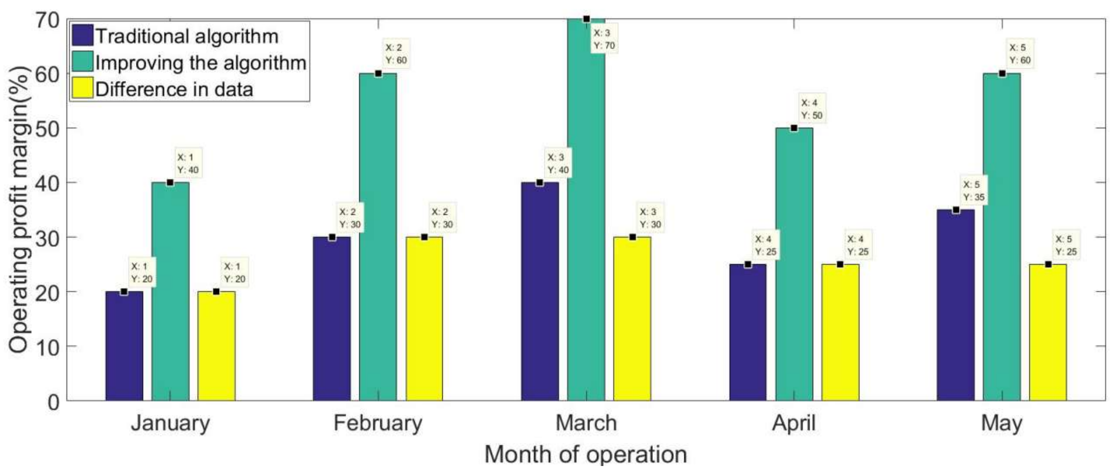

Figure 4: Comparative analysis of operating profit margin data

Through the comparative analysis chart of return on investment data and operating profit margin data, it is obvious that in the actual financial performance evaluation, the improved genetic optimization algorithm was better than the traditional genetic optimization algorithm. In terms of return on investment, the highest return of traditional algorithms in investment projects was 70%; the lowest return was 60%; the average return in five projects was 65.4%. The highest return rate of the improved algorithm in the investment project was 80%. The lowest return rate was 70%. The average return rate in the five project investments was 75%. Based on the difference between the return on investment of each project, the overall average return increased by 9.6% after the application of the improved algorithm. In terms of operating profit margin, the monthly performance brought about by the traditional algorithm was not optimistic compared with that by the improved algorithm. In the operating profit performance data of traditional algorithm from January to may, the highest operating profit margin was March, with a profit margin of 40%. The lowest operating profit margin was January, with a profit margin of only 20%. In the five months of operating profit, the average monthly operating profit margin was 30%. In contrast, in the operating profit performance data of the improved algorithm from January to may, the highest operating profit margin was also March, with a profit margin of 70%. The lowest operating profit margin was January, with a profit margin of 40%, and the average monthly operating profit margin was 56% in the five months of operating profit. Compared with the average monthly operating profit margin of the traditional algorithm, the average monthly operating profit margin of improved algorithm increased by 26%. Through the above data, it is enough to show that the improved genetic optimization algorithm had a significant improvement in financial performance.

III. C. Comparison of Detailed Data of Financial Performance Evaluation Indicators

In the process of the operation of the company, financial performance and other factors may directly or indirectly affect the operation income of the company, including but not limited to the investment income and operating profit income of the enterprise. In the financial performance of enterprises, whether the financial performance evaluation indicators are perfect directly affects the accuracy of financial performance evaluation, thus affecting the financial returns of enterprises. Therefore, whether the financial performance evaluation indicators are perfect and accurate is the core issue that the financial performance system needs to consider. The following is a comparative analysis table of various data indicators between the financial performance system using the traditional genetic algorithm and the financial performance system using the improved genetic optimization algorithm. The comparative analysis table of various data indicators of the system is shown in Table 3:

Table 3: Comparative Analysis of various data indicators of the system

Unit(number)	Traditional financial performance systems			Optimized financial performance systems		
Data category	Operational data	Leave data	Data on Wages	Operational data	Leave data	Data on Wages
Department1	5	6	5	8	10	9
Department2	4	5	5	9	10	9
Department3	3	4	5	10	10	9
Total	12	15	15	27	30	27
Mean	4	5	5	9	10	9

Through the comparative analysis of various data indicators in the system, it can be found that the number of evaluation indicators in the traditional financial performance system of each department was relatively small, and the largest number of evaluation indicators was the relevant evaluation data on leave and wages, all of which were 15. In the three evaluation departments, the average number was 5 for each department. The smallest number of evaluation indicators was the relevant evaluation data on operation, with 12. The departments had an average of only 4 evaluation indicators. In the optimization of financial performance system, the machine learning technology in the improved genetic optimization algorithm learned and innovated according to the existing data, and derived the relevant evaluation indicators data. The largest number of evaluation indicators to optimize the financial performance system is the relevant evaluation data on leave, the number is 30, in the three evaluation departments, the average number was 10 per department. The smallest number of evaluation indicators was the relevant evaluation data on operation and wages, with 27. The departments had an average of 9 evaluation indicators. In terms of quantity, the optimized financial performance system had more reference data for financial performance evaluation. The more evaluation indicator data, the more accurate the analysis of enterprise revenue and expenditure fluctuations. The following is a comparative analysis chart of enterprise financial benefits formed by an enterprise according to the number of evaluation indicators, as shown in Figure 5:

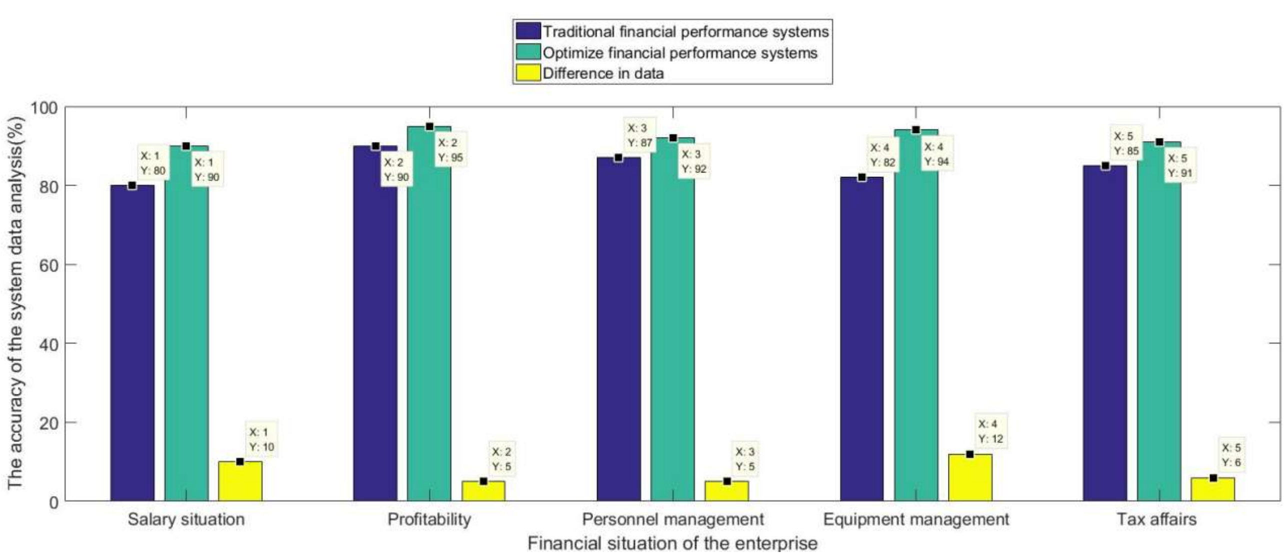

Figure 5: Comparative analysis of financial benefits of enterprises

In the comparative analysis chart of enterprise financial benefits, it can be seen that the accuracy of the traditional financial performance system in the analysis of various financial data items was lower than that of the optimized financial performance system. In the traditional financial performance situation, the lowest accuracy rate of situation data analysis was salary situation and the accuracy rate of data analysis was 80%. The highest accuracy rate of situation data analysis was profitability and the accuracy rate of data analysis was 90%. The comprehensive accuracy rate of data analysis of traditional financial performance system was 84.8%. The optimization of financial performance system has improved in performance data analysis. In the optimization of financial performance, the lowest accuracy rate of situation data analysis was salary situation and the accuracy rate of data analysis was 90%, which was higher than traditional financial performance data by 10%. The highest accuracy rate of situation data analysis was profitability, with an accuracy rate of 95%, which was also higher than traditional financial performance data by 5%. Combined with the data, after calculation, the overall comprehensive average data accuracy of the optimized financial performance system was higher than that of the traditional financial performance system by 7.6%. That is to say, in the accuracy of financial performance evaluation indicators, the traditional financial performance algorithm was insufficient.

III. D. Comparison of Dynamic Data of Financial Performance

In the enterprise financial performance system, the capital flow of each department is changing accordingly all the time, and the change of capital means the change of capital data. Combined with the fact that enterprises mostly take intelligent office as the main office mode, in terms of capital flow data, the number of enterprises that use manpower to record capital data is gradually decreasing, and most enterprises upload and enter data through intelligent computers, which leads to the dynamics of capital data. The following is the comparative analysis figure of dynamic timeliness of liquidity data in financial performance system, as shown in Figure 6:

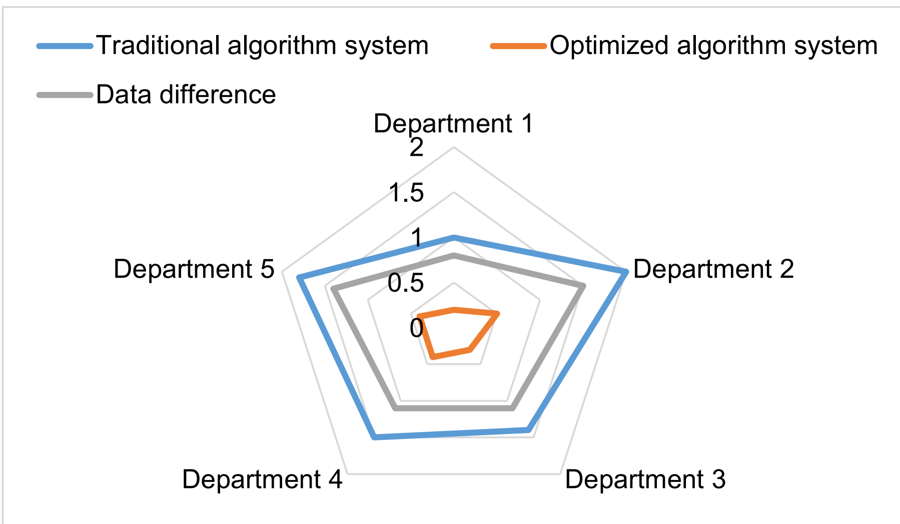

Figure 6: Comparative analysis of dynamic timeliness of liquidity data in financial performance system

In the comparative analysis figure of dynamic timeliness of liquidity data in financial performance system, the dynamic timeliness of liquidity data in traditional algorithm system was generally longer. Among them, the timeliness of data warehousing in department 2 was the longest and the data took 2 hours to entry system. The department with the shortest timeliness of data warehousing was department 1, and the data took 1 hour to entry system. In contrast, the dynamic timeliness of liquidity data in the optimization algorithm system was faster. The longest timeliness of data warehousing was department 2 and the data took 0.5 hours to entry system. The shortest timeliness of data warehousing was department 1 and the data took 0.2 hours to entry system. Considering the dynamic timeliness of liquidity data in various departments, the average data entry time of the optimization algorithm system was 1.18 hours shorter than that of the traditional algorithm system. According to the above data, it can be explained that the optimization algorithm system completely surpassed the traditional algorithm system in the dynamic data processing of financial performance funds, and greatly improved the efficiency of understanding the real time situation of financial capital flows among enterprise departments.

IV. Conclusions

Compared with the traditional genetic optimization algorithm, the improved hybrid genetic optimization algorithm was not only more intelligent in algorithm, but also could learn and analyze data through machine learning technology. In data decomposition, there was also simulated anneal algorithm to help genetic algorithm decompose data, which greatly improved the data calculation efficiency of genetic algorithm. In practical application, whether in the data processing of enterprise investment return or enterprise operating profit, it was slightly inferior to the hybrid genetic optimization algorithm. In the data indicators of the system, the performance differences between the two algorithms were very obvious. In addition, in terms of the dynamic timeliness data of liquidity data in financial performance system and the comparative analysis of enterprise financial benefit data, it was enough to show that the traditional genetic optimization algorithm was not fully optimized, and there was still a lot of optimization space. Of course, this does not deny that traditional genetic optimization algorithms are not desirable. The development and innovation of things are always relative. The development of anything needs to conform to the process of the times. In today’s era, early genetic optimization algorithms are not enough to meet the needs of modern systems, and should be improved and developed. Through the above tests and data comparison of the improved hybrid genetic optimization algorithm, it can be concluded that the improved hybrid genetic optimization algorithm could indeed make the financial performance evaluation indicators more intelligent and efficient in the enterprise financial performance evaluation system and achieve better results in the field of financial performance evaluation.

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