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The Performance Forecast Index of Innovation Investment Fund Based on Animal Algorithm

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Abstract: At the point when individuals decide to put resources into protections or other gamble resources, there are two issues that they are generally worried about: the normal profit from resources and the dangers. In the beginning phase of the improvement of monetary hypothesis, how to decide the gamble and return of speculation is an issue that financial backers need to earnestly settle. Economists have been studying how to use quantitative methods to continuously improve the investment theory and the practical operation of the theory. These studies have made great progress in the theory and application of portfolio theory. At present, many meaningful attempts have been made in the research and practical application of portfolio theory in China, but none have achieved good results. In order to better solve the problem of performance prediction indicators after investment funds, this paper deliberately introduces the current most popular animal algorithm-ant colony algorithm. The ant colony algorithm can well predict the investment results, with an accuracy rate of more than 95% and a failure rate of less than 3%. It solves the problems that investors are most concerned about. I hope to play a certain role in promoting the development of China's investment industry.

1. Introduction

Whenever individuals decide to put resources into protections or other gamble resources, there are two issues that they are generally worried about: the normal profit from resources and the dangers. With the advancement of present day PC innovation, monetary examination has entered another stage. The utilization of PC innovation to the field of portfolio streamlining has incredibly advanced the improvement of current resource determination hypothesis. With the ceaseless improvement of present day advancement innovation, intelligent heuristic optimization methods such as ant colony algorithm have appeared. This type of method has many superior performances: first, such optimization methods generally do not have large restrictions on the solution object, and can directly operate the optimization object; second, they generally have inherent parallel distribution, and use probabilistic search The optimal method has higher optimization efficiency. Third, because these algorithms are derived from biological systems in real life, these algorithms are intelligent, can adaptively adjust the search direction, and efficiently find the global optimal solution. First of all, the current research results are limited to solving the portfolio optimization problem of less than ten securities, which cannot reach the level of practical application. Secondly, the current research only considers the return as a factor for portfolio optimization, and ignores the impact of important factors such as risk and liquidity, which need to be improved. Furthermore, the current research results are limited to static analysis and lack of applications in dynamic analysis. Therefore, it is necessary to further study how to better combine heuristic algorithms such as ant colony algorithm with portfolio optimization problems, and design excellent heuristic algorithms to solve large-scale portfolio problems.

Investment is inherently risky, and in order to reduce it, many people have studied it. Lijun studied the optimal investment and risk control of insurance companies under random factors. Insurance companies allocate their wealth to risk-free bonds and risky assets, whose risk and volatility depend on the factor process. Risk processes are modeled by jump diffusion with state-dependent jump metrics. By maximizing the expected power utility of terminal wealth, we characterized the best strategies for investment and risk control, analyzed the classical solution of HJB PDE, and proved the verification theorem. In fact, the vast majority of investors cannot afford a lot of losses [1]. The Wookjae study looks at the reserve funds part of abundance amassing by assessing individual financial backer contrasts in monetary gamble resistance and value. The outcomes give a system and technique to future exploration on abundance disparity, venture conduct, and chance mentalities. For scientists, strategy creators, social activists, monetary guides, monetary counselors, and instructors, the capacity to correspondingly bunch US inhabitants while examining family and macroeconomic abundance profiles might be a significant as welll [2] . Hong's research on high-tech companies' research and development investment will have an impact on corporate risk, but the effect will be different under different funding sources. The aim is to study the relationship between financing sources, R & D investment and corporate risk. Empirical results show that there is a significant positive correlation between the endogenous financing rate and R & D investment, and the asset-liability ratio has a significant negative impact on R & D investment [3]. Shuming considered the issue of portfolio improvement consolidated financial plan venture under the administrator's gamble resilience vagueness. To catch the dynamic elements driven by the vagueness of hazard resilience, a two-stage versatile streamlining model was created. Spending plan distribution is the principal phase of direction and it is made prior to getting the real gamble resilience of every director. The portfolio choice made by every administrator is the second phase of direction, which is reasonable for the director's gamble resilience [4].

In this paper, a comparative study of the ordinary algorithm and the ant colony algorithm, and combining the ant colony optimization algorithm with the investment optimization theory, will provide a very effective means and tool for solving the problem of portfolio optimization. Through investigation, it is found that the ant colony algorithm has achieved very good results. I hope that the research in this article will have a certain role in promoting China's investment industry.

2. Proposed Method

2.1 Basic Principles of Ant Colony Algorithm

In recent years, many bionic algorithms have appeared, such as ant colony algorithm, immune algorithm, genetic algorithm and so on. This article is to choose the ant colony algorithm to solve the portfolio optimization problem, in order to get a better method to solve the portfolio optimization problem [5].

The ant colony algorithm was originally a search algorithm used to find the optimal path. As we all know, the behavior and ability of a single ant is very simple, but the ant colony composed of these simple individuals can often accomplish many extremely complex tasks. For example, no matter how complex the environment is, ant colonies can always find the shortest path to move food. After observation and research, people found that when searching for food, ants will release a substance called pheromone on the path it passes. It is through this material that information is transmitted between individual ants at all times. The principle is this: an ant can leave pheromone on the path it passes during the movement, and can also sense the pheromone left by other ants, and according to the distribution of pheromone on each path Decide your own direction of movement. Therefore, in this way, a positive feedback of information is generated in the collective behavior of the ant colony. The specific operation mechanism is as follows: Assume that there are two roads leading from the ant's nest to the food location. To simplify the analysis, it is assumed that the number of ants who take these two roads is the same at the beginning. When the ants reach the end point along a road, they will return immediately. In this way, the time for the ants to go back and forth once on a short path is short, which also means that the frequency of repetition is fast, so the number of ants that walked in a unit time is more. Naturally, there will be more pheromone spilled. The ants will choose the direction with more pheromone when they move, so the ants passing here will increase, which will attract more ants to gather and sprinkle more pheromone; the long path is exactly the opposite. Therefore, as time goes by, more and more ants gather on the shorter path until all the ants are concentrated on the shorter path, so the ant colony finds the shorter path. At the same time, the ant will have a certain probability not to go to the place with higher pheromone, and choose other paths with lower pheromone. This behavior can be understood as a behavior of exploring new routes. If this kind of exploration can shorten the length of the path, then according to the principle just mentioned, more ants will be attracted to this better path over time. Therefore, this exploration can prevent the ant colony from converging on the local shortest path and missing the global shortest path, that is, the process of ant foraging will gradually converge on the global optimal solution. It is through this exchange of information between ants to determine the optimal route when searching for food [6-7].

When no ants find food in the early stage of the search, the ant colony can carry out the search work relatively effectively. The mystery lies in the special movement rules of ants, especially when there are no pheromone on all its routes. First of all, the search of the ants should try to maintain a certain directionality, so that the ants can move as far forward as possible (at the beginning, this front is a randomly fixed direction), rather than searching for no purpose; second, the movement of the ants needs With some randomness. In this way, the ant's search has a large direction and is also randomly interfered.This makes the ants have a certain purpose and does not lack new exploration, especially it can make the ant colony according to the obstacles. The distribution can effectively adjust the moving direction. This explains why no matter how complex the environment is, ant colonies can always find well-hidden foods [8].

2.2 Description of Artificial Ant Colony Algorithm

It can be seen from the principle of biological ant colony foraging that a single ant can also find the shortest path between the ant's nest and the food source, but this possibility is extremely small. Only when many ants gather together to form an ant colony can the ant colony's swarm intelligence become prominent. At this time, the ant colony has the ability to find the shortest path between the anthill and food source in the shortest time. In the process of ant colony foraging, they adopted an indirect communication method-releasing pheromones on the path they passed, and the remaining ants made judgments by sensing the strength of the pheromone. Pheromone plays the role of information transmission in this process. It connects each individual in the ant colony, and each individual also communicates with each other through pheromone. This kind of media is called

Stigmergy. Scholars applied this collaborative mechanism of ant colony foraging to the Artificial Multiagent Model (AMM) to get the artificial ant colony algorithm. In the artificial ant colony algorithm, state variables are used to represent the state of the problem at a certain moment, and then the artificial body makes judgments and selections and updates the state variables by sensing the local state information, just as the ants are in the process of foraging The pheromone left by the ant was sensed before. At this time, the artificial ant colony state variable changes like the pheromone behavior on the biological ant colony update path. In the foraging behavior of biological ant colonies, the positive feedback mechanism of information is used to find high-quality problem solutions. Artificial ant colonies mimic this positive feedback mechanism to make the problem solutions optimal. At the same time, the ants in the artificial ant colony algorithm are given part of the memory function, can record the information on the path, and have the ability to sense some heuristic information [9-10].

2.3 Difference between Artificial Ant Colony and Biological Ant Colony

Artificial ant colony algorithm has the same points as biological ant colony:

(1) Artificial ant colony and biological ant colony are a cooperative group. Each artificial ant can provide a solution to the problem, but the optimal solution to the problem is obtained through the cooperation of the ants.

(2) Artificial ant colony and biological ant colony must complete certain tasks. Artificial ants need to complete the optimization of the given problem, and the biological ant colony should find food at the fastest speed, and find the shortest path between the ant nest and the food source. In reality, ants cannot jump from one area to another. They can only search step by step from one area. The same is true for artificial ants, which can only be transferred to neighboring cities [11] .

(3) Artificial ant colonies, like biological ant colonies, communicate indirectly through sensing pheromones in the surrounding environment. Artificial ant colony imitates biological ant colony to release pheromone on the path it passes, and perceives the concentration of pheromone on the path to make a choice.

(4) Artificial ant colonies mimic the positive feedback mechanism of biological ant colonies during foraging. In the iterative process of the artificial ant colony, it finds better solutions by sensing the pheromone, and further strengthens these better solutions, so that the better solutions of the problem continue to evolve towards the optimal solution.

(5) Artificial ant colonies have the same pheromone volatilization mechanism as biological ant colonies. In the artificial ant colony algorithm, a pheromone volatility function is designed just like the biological ant colony. The pheromone volatility function can make ants less and less affected by previous experience, which is conducive to ants searching towards new areas and avoiding precocity [12].

(6) Do not make predictions for the future, and transfer according to the probability of choosing the direction. Artificial ant colony, just like biological ant colony, uses local information to choose the direction of transfer in a probabilistic way, based on which to obtain a solution to the problem, without any prediction of the future state.

In addition to the similarities between the above six artificial ant colonies and biological ant colonies, the artificial ant colony algorithm also has some characteristics that biological ant colonies do not have. The main points are as follows:

(1) The space where artificial ants exist is a discrete state, and the transfer of artificial ants is actually from one discrete point to another.

(2) There is a special storage mechanism for artificial ants, in which the past behaviors of artificial ants are stored.

(3) The artificial ant colony algorithm establishes a pheromone update function, and this function determines the quality of the problem solution.

(4) In biological ant colonies, ants release pheromones during the process of movement, while in artificial ant colony algorithms, the time to release pheromone varies with the designer's solution to the problem. Artificial ant colony algorithm can first establish a feasible solution to a problem, and then update the pheromone.

(5) In order to improve the ability to solve problems, artificial ants are given some abilities that biological ant colonies do not have, such as forward-looking, local optimization, return to the original path, and so on.

2.4 Basic Principles of Ant Colony Algorithm

Investors seek to maximize the return when the risk is constant, or minimize the risk when the return is constant. The model takes this goal as the starting point and combines the characteristics of the ant colony algorithm to set the pheromone rules to gradually guide the ant colony to find the optimal investment portfolio.

2.5 Efficient Market Hypothesis

An early utilization of PCs in financial aspects during the 1950s was the investigation of time series information. Researchers who concentrate on the monetary cycle accept that following the improvement of specific financial factors can explain and foresee the qualities of monetary advancement in the blast and downturn period. Along these lines, changes in securities exchange costs normally become the object of its investigation. (1953, Maurice Kendall) By concentrating on the recommendation that "the stock cost can mirror the pinnacle and valley of the economy based on mirroring the organization's possibilities," he was amazed to observe that there is no anticipated worldview at stock costs, which laid The premise of the proficient market theory. The effective market speculation was deliberately proposed by Eugene Fama in 1970. This theory holds that in a productive market, stock costs completely mirror all known data and can completely and openly reflect changes in data, and applicable data on protections can be completely revealed and equitably dispersed, and everything financial backers can acquire homogeneous data whenever. Furthermore, can utilize data really. Along these lines, under the condition that the market is proficient, specialized investigation and crucial examination won't produce non-market expenses. Contingent upon the meaning of "all suitable data", the proficient market speculation can commonly be isolated into three structures:

(1) Weakly efficient market hypothesis defines "all available information" as historical information. Historical data on securities that are open and easily available have no effect on the current and future price changes of securities. We can check the change pattern of the security price to see if it is related to the historical price. If the correlation coefficient is close to zero, it means that the stock price in the two days before and after is irrelevant, that is, the stock price moves randomly, and the market reaches weak-form efficiency.

(2) The semi-strong efficient market hypothesis defines "all available information" as historical information and public information. For investors, in the semi-strong and efficient market, excess profits cannot be obtained through analysis of public information. We can use the event research method to statistically analyze the abnormal events and abnormal returns data. If the abnormal returns are only related to the events disclosed on the day, the market is semi-strong.

(3) The strong efficient market hypothesis defines "all available information" as historical information, public information, and internal information. For investors, profits cannot be obtained from public and non-public information analysis, so inside information is useless. The test of the

strong effective capital market mainly examines whether the "insider" can obtain extraordinary profits when participating in the transaction. If not, the market has reached a strong effective.

The effectiveness of investment strategies is also different in different forms of efficient markets:

(1) Technical analysis techniques in weakly efficient markets will not be able to consistently generate excess returns, although some forms of basic analysis may still provide excess returns. The stock price does not show serial dependence, which means that there is no "pattern" of asset prices. (2) The fundamental analysis on the semi-strong effective market is invalid, and inside information may obtain excess profits. Fundamental analysis of enterprises mainly analyzes a company's financial statements (mainly assets, liabilities and profits), its competitors and market conditions. The fundamental analysis of macroeconomics focuses on factors that affect interest rates, output, and employment. Fundamental analysis targets financial forecasts based on historical and current data to value company stocks and predict their possible price evolution. Therefore, the semi-strong efficient market hypothesis holds that most fundamental analysis is also doomed to fail. Even if investors use exhausted methods to analyze public information in the market, it is impossible to obtain extraordinary returns.

(3) Insider trading in a strong and efficient market is invalid, and even "insiders" cannot obtain extraordinary profits.

3. Experiments

3.1 Test Object

Investment is an extremely complicated industry, which requires not only vision but also courage. Because when people choose to invest, there are two problems: the expected return on assets and the risk. In the early stage of the development of financial theory, how to determine the risk and return of investment is an issue that investors need to solve urgently. With the continuous development of modern optimization technology, intelligent heuristic optimization methods such as ant colony algorithm have appeared. This type of method has many superior performances. First, such optimization methods generally do not have large restrictions on the solution object, and can directly operate the optimization object. Second, they generally have inherent parallel distribution and use probabilistic search. The optimal method has higher optimization efficiency. Third, because these algorithms are derived from biological systems in real life, these algorithms are intelligent. This article compares the performance forecast of innovative investment funds based on ant colony algorithm and ordinary algorithm to find a more secure method.

3.2 Design and Implementation of Experiments

The market is completely open, that is, the securities market is a completely competitive market; n stocks are selected for investment in the stock market; there is an upper limit on the number of stocks that can be purchased; the total assets owned by investors are certain, and they invest in The amount of the stock market is also determined; when buying new securities, another one or several securities of the same funds that have been held must be sold; there is no liquidity risk, that is, investors can sell securities according to their own wishes When buying and selling, there is no phenomenon of being unable to buy or sell. To simplify the optimization process, this article only optimizes the portfolio model in a static environment. Under the above conditions, ant colony algorithm and ordinary algorithm are used to calculate the investment performance. After comparison, we found a more secure method.

4. Discussion

4.1 Comparison of Prediction of Two Investment Results

As can be seen from Figure 1, the accuracy of the results predicted by the ant colony algorithm is significantly higher than that of ordinary algorithms. The prediction accuracy rate of the ant colony algorithm is all above 95%, while the prediction results of the ordinary algorithms are all below 80%. Obviously, the prediction of ant colony algorithm is better than ordinary algorithms.

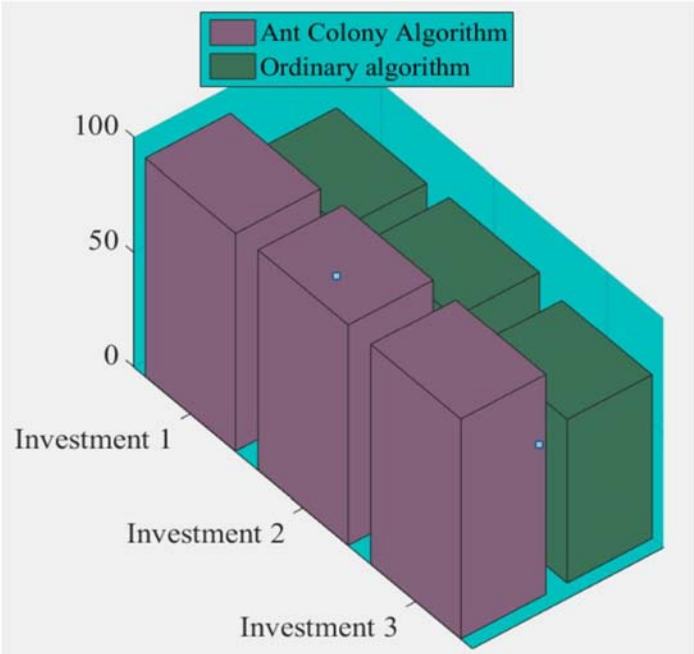

Figure 1. Accuracy of prediction by two algorithms

4.2 Comparison of Investment Failure Rates between Ant Colony Algorithm and Ordinary Algorithm

Every investment has certain risks. Minimizing investment failure is the most pleasing to every investor. It can be seen from Figure 2 that the investment failure rate of ordinary algorithms is more than 15%, and the investment failure rate of ant colony algorithm is less than 3%, and the investment failure has dropped to almost 0.

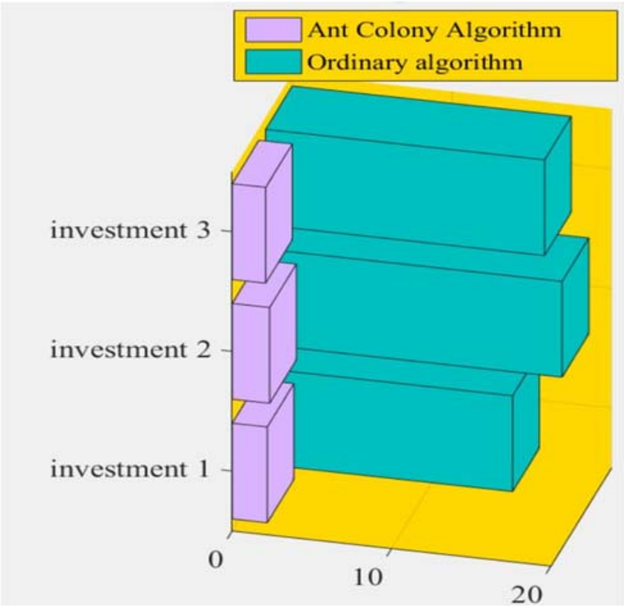

Figure 2. Investment failure rate of two algorithms

4.3 The Profitability of Two Algorithmic Investments

The ultimate purpose of investment is to make money. As can be seen from Figure 3, the profit rate of the ant colony algorithm is above 85%, while that of ordinary algorithms is below 50%. The main reason is that the ant colony algorithm has a higher success rate than ordinary algorithms and reduces investment failures, so the profits naturally increase.

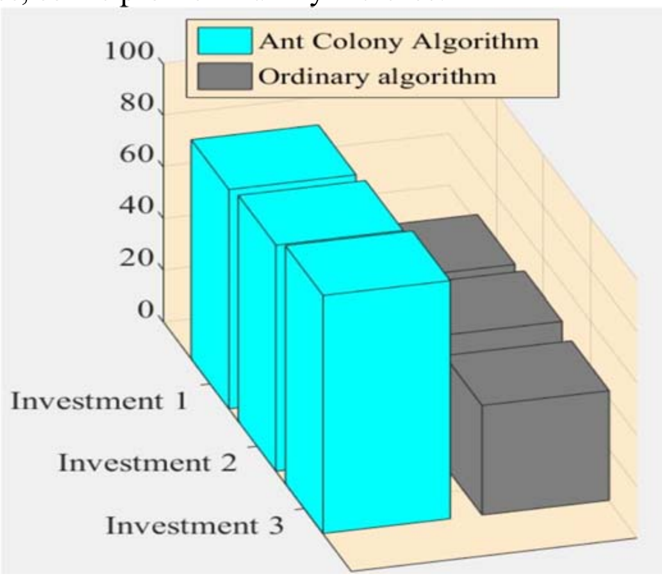

Figure 3. Profit rate of investment in two algorithms

4.4 User Evaluation

It can be seen from Figure 4 that in recent years, the ant colony algorithm's praise rate has become higher and higher, and users have become more and more satisfied with its use. In 2019, the user praise rate reached 98.6%. As can be seen from Table 1, more and more users are using the ant colony algorithm. By 2019, the number of users has exceeded 1,000, and the ant colony algorithm has won user satisfaction.

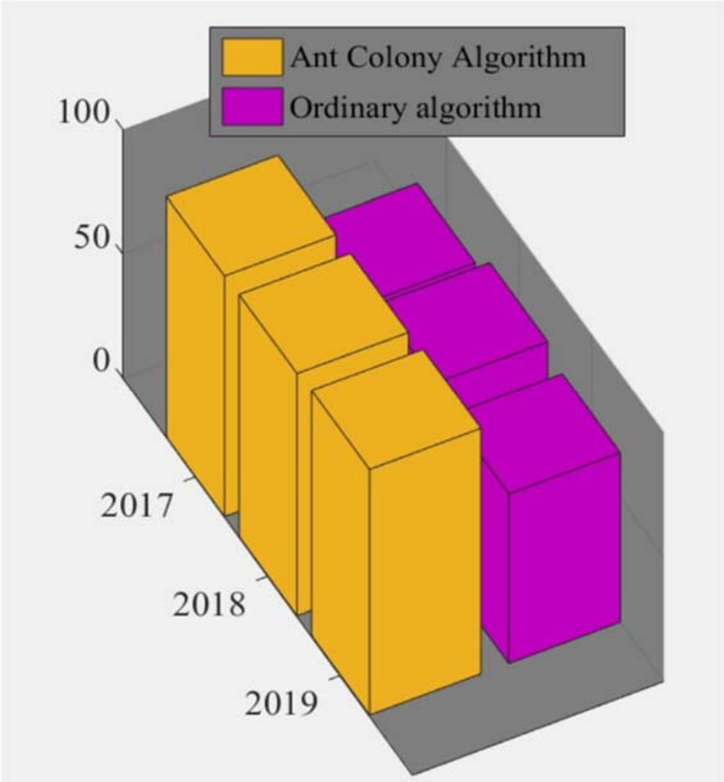

Figure 4. Positive rate of two algorithms

Table 1. Number of users of ant colony algorithm

Years	User Count	Expected use
2017	80	30
2018	560	800
2019	1032	3860

5. Conclusions

Based on the portfolio theory model proposed by Markowitz, this paper proposes an ant colony algorithm to optimize the large-scale portfolio problem. At the same time, the multi-objective optimization continuous domain ant colony algorithm is used to consider the two indicators of profit and risk to build a model solution. Then based on the above model, considering the practicality of modern securities portfolio theory in China, a dynamic investment model is established to optimize the large-scale portfolio problem of the domestic securities market. Solving portfolio optimization can be reduced to a multi-objective continuous domain optimization problem with constraints. In order to simplify the analysis, some simplified settings are adopted in the initial stage of the modeling, and practical factors such as transaction costs and minimum transaction units are not considered for the time being. In the subsequent model expansion, these factors are considered gradually to enrich the model. Based on the in-depth study of existing portfolio models at home and abroad, this paper improves the model and combines it with the special environment in which our financial market is located, making the model suitable for the investment environment of our financial market. For the research of ant colony algorithm, this article starts from the most basic ant colony, analyzes the optimization method of the basic ant colony algorithm, and improves it. It successfully combines the improved portfolio model with the ant colony algorithm and finds the problem. Optimal solution. In the empirical analysis stage, the improved model was used to obtain two sets of investment portfolios, and the two portfolios were analyzed in terms of benefits, risks, costs, and suitable populations. The results showed that the results obtained were consistent with the actual situation. Combining the improved multi-objective optimization continuous domain ant colony algorithm with the portfolio model can overcome many weaknesses of previous research results. The number of securities in the portfolio optimization model based on ant colony algorithm is greatly increased, and the optimal solution can be searched considering more economic factors than in the past. It turns out that this method is more effective. By comparing investment portfolios with market portfolios and no-strategy portfolios. When the risk level is the same, the portfolio obtained by the ant colony algorithm has a higher return. This shows that the model established in this paper can find better combination strategies.

Through investigation, this paper finds that in the field of securities investment, the combination of artificial intelligence and human wisdom may be the main way of future investment. When an investor needs to make an investment, first use artificial intelligence to establish a portfolio and analyze the advantages and disadvantages of each portfolio. Investors use this as a reference, and then the investor makes investment decisions based on personal investment experience and the actual economic environment. . The combination of artificial intelligence and portfolio model will be the focus and difficulty of research in the field of securities investment for a period of time. This paper attempts to combine intelligent optimization algorithms with portfolios and has achieved certain results. The combination of the Internet and the financial industry is driving the transformation of the traditional financial industry, and the rise of Internet finance is the general trend. Since Ant Financial Group launched Yu'ebao in 2013, the Internet financial market has flourished. New types of investment and financing methods such as P2P and crowdfunding have begun to rise, and the scope of investors' investment and wealth management has expanded, and is no longer limited to traditional financial products such as bank deposits, stocks, futures, and funds. In this paper, Yuebao, a representative product in Internet finance, is included in the scope of investment targets, which provides new ideas for investors to invest and manage wealth.

There are still many shortcomings in this article, and some issues need further study. In order to simplify the analysis process, a number of realistic conditions have been ignored, such as not considering transaction costs and minimum transaction units. Therefore, there will inevitably be some distortion in the modeling process, which will have a certain impact on the practicability of the model. In order to better study the portfolio optimization problems of the real securities market, these real conditions can be considered in further research, the model structure can be refined, and the degree of model simulation can be improved to improve the optimization effect of the model. In the process of establishing a dynamic portfolio model, other stock selection criteria and stock selection strategies can also be considered. This article adjusts the dynamic portfolio structure based on the returns and risk profile of all the securities selected in the past 60 days. In order to simplify the model, other factors have been ignored. In reality, there are many factors that will affect the adjustment of dynamic portfolio structure (such as liquidity factors), so there is still the possibility of further optimization. There are many parameters in the model, and the size of these parameters directly affects the search efficiency and results of the model. Therefore, it is necessary to study these parameters and determine which parameter ranges are optimal to improve model performance. The calculation of the yield data is based on the daily closing price, and in real life, investors can trade at any point in the trading day.Therefore, the price of the stock when buying and selling is still required. discuss. The investment behavior of securities is a dynamic process, and returns and risks are generated in the future.The data selected in this article are past data for investment behavior. These data have certain predictive effects on the future but are not comprehensive. Therefore, The research on the factors affecting the future price of securities is of great value.

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