Application of Ant Colony Algorithm in Multi-objective Optimization of Portfolio Investment

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Abstract

Ant colony algorithm is a kind of artificial intelligence algorithm, which is widely used in solving combinatorial optimization problems, and achieves the expected results. In this paper, we use the ant colony algorithm to obtain the effective boundary of the portfolio, that is, the Pareto frontier, under the multi-objective optimization. This is an ant colony algorithm in a multi-objective optimization application field of a study, try and expand. The main work of this paper is to establish the model of portfolio investment problem under ant colony algorithm. Based on the multi - objective optimization problem, the continuous domain ant colony algorithm is used to improve the heuristic function, adaptive pheromone, maximum and minimum pheromone range. The improved ant colony algorithm is implemented, and the effective boundary of the securities portfolio is obtained. At last, the parameters in the ant colony algorithm are analyzed and the function of the parameters is clarified. The investment of securities is very meaningful in theoretical research and practical application, and the ant colony algorithm is applied to the multi - objective optimization problem of securities portfolio. It is also a meaningful attempt to expand the application of ant colony algorithm. The research of this paper has certain theoretical and practical value.

Keywords: Ant colony algorithm, portfolio investment, multi-objective optimization, Pareto frontier

1. INTRODUCTION

As we all know, financial problems are large, complex, and infinite, and the results of high precision requirements. For some complex financial problems, from the perspective of theoretical analysis and practical application of the operability of the study, the two are quite different, and the theoretical analysis of the method is often not suitable for practical applications (Bastianiet al., 2015). In recent years, with the rapid development of computer technology, there has been a surge of research on the use of computers to solve practical financial problems in the financial field. This will combine computer and financial research to the forefront of financial research and application. It has become the main way of financial research field based on theoretical analysis and the use of computer technology to achieve and test methods. Ant colony algorithm is a kind of artificial intelligence optimization algorithm, and its proposition is inspired by the behavior of ants in nature searching for food. There are a number of ants in the algorithm, which can exchange information to construct the solution path, so as to improve the validity and satisfaction of the solution, and then achieve the purpose of optimization. At present, ant colony algorithm is widely used in many practical optimization problems, because ant colony algorithm is not only robust, but also can be combined with the application field well (Lejeune et al., 2016). Ant colony algorithm has great potential for development, and it can be well combined with other algorithms.

China's securities market has a large population of individual investors. Fund management in metropolitan areas has become very common nowadays. The reason why most investors choose funds is that it is specialized in managing money, dispersing risks and sharing risks. Expected return and risk are the two most important concerns for people to invest (Del Sagrado et al., 2015). Generally, they want the greater the risk when the risk is certain, or the less the risk is, the better the risk is. However, the range of risks that different investors can take is different. Therefore, this paper finds out the frontier of Pareto, which enriches the optional range of investors and helps them find the most satisfactory investment plan based on the double objective optimization ant colony algorithm with profit and risk. Therefore, the research of this paper is of practical significance. At the same time, it is also a meaningful attempt of ant colony optimization in the application field of multi-objective optimization.

2. MULTI-OBJECTIVE OPTIMIZATION

2.1 Definition of multi - objective optimization

The multi-objective optimization problem (MOP) was proposed by Pareto, a famous French economist in 1886. After 1970, multi-objective programming became a formal branch of mathematics. Since then, the theory has really developed. So far, multi-objective optimization has been widely used in a variety of issues, such as economic, engineering, management, military and so on. The basic meaning of multi-objective optimization is to have multiple goals in a problem to achieve, and these goals are conflicting and constrained (Vassiliadis,2009). The purpose of optimization is to find a set of values within the scope of the problem, making the user most acceptable. The biggest difference with the single-objective optimization problem is that the arbitrarily two solutions of the multi-objective problem are not necessarily different from each other, and are semi-ordered. The single-objective optimization problem is completely ordered.

2.2 General model of multi - objective optimization problem:

$$\min F(x) = [f_1(x), f_2(x), ..., f_m(x)]^T \tag{1}$$

$$\begin{aligned} s.t. \quad & g_u(x) \geq 0 \quad u = 1, 2, ..., p \\ & h_v(x) \geq 0 \quad v = 1, 2, ..., q \end{aligned} \tag{2}$$

In the formula (1): $f_t(x)$ is the objective function ; $g_u(x)$ and $h_v(x)$ are constraints.

2.3 Decision space and objective function space

Decision space is the space composed of all the parameters of the objective function satisfying the constraints. The decision space feasible domain is described as follows:

$$D_x = \{X \in R^n \mid g_u(x) \geq 0, h_v(x) = 0\} \tag{3}$$

In the formula (3), u=1, 2,…,p; v=1,2,…,q.

An objective function space is a space composed of points on all decision spaces passing through the mapping of objective functions. The description of the feasible region of the target space is as follows:

$$D_F = \{F \in R^m \mid F = [f_1(X), f_2(X) ... f_m(X)]^T, X \in D_x\} \tag{4}$$

2.4 Pareto front

The Pareto frontier is a nonprofit set of multi-objective optimization problems, where noncritical solutions are also called Pareto solutions. That is, in the objective function of the feasible domain can not find a point, so that it dominates the Pareto front point. Pareto solution is described in the mathematical language as follows:

$X^P \in D_x$, $\neg\exists X \in D_x$ makes $F(X) \leq F(X^p)$ set up.

3. SECURITIES PORTFOLIO

3.1 Definition and fundamental principles of securities portfolio

The portfolio is simply a matter of investing different amounts of money in different risk assets, where each asset is part of the total capital to achieve the risk of diversifying risk and ensuring the benefits. "Do not put all the eggs in a basket," the argument has long existed, but only experience that there is no theoretical basis (Duan et al., 2016). In 1952, Markowitz finally gave the theoretical basis of this argument. Based on the mathematical theory of quantitative thinking, he explained the investment portfolio in a mathematical way to reduce the correctness and validity of the risk. In his proof, the volatility of stock returns is proposed and used as a bold measure of risk measurement. Based on this, the analysis method of the specific portfolio theory is given, namely the mean-variance model. This is a number of financial areas of a major initiative, it has made the study of modern finance.

The mean-variance model is a new initiative based on the idea of quantitative analysis to solve the problem of portfolio, which is the basis of all portfolio mathematical analysis. "Portfolio" usually refers to the general term of a number of individual resources, and a portfolio refers to the general term of a number of securities. Securities usually include bonds, stocks, etc. The portfolio theory suggests that the combined risk is related to the number of constituent securities in the portfolio (Giannakouris et al., 2010). The relationship between the two is that the combined risk decreases as the number of securities it contains increases, and the correlation coefficient between the securities is smaller and the risk is small. Although there is theoretical support, it is still difficult to choose how stocks and assignments to form a satisfactory combination and how to make decisions in a combination.

3.2 Management of securities portfolios

Management of securities portfolio can be divided into passive management and active management of the two categories. Passive management uses a "buy-and-hold" investment strategy that uses long-term stability to hold a number of indexed securities portfolios to gain the average return on the market for the purpose. On the contrary, active management theory that the market is not entirely effective, that is to say there is a lag in the market was overvalued or underestimated securities (Xing et al., 2014). The purpose of proactive management is to identify these securities and forecast market conditions, and then adjust the portfolio to get higher than the average market returns.

The following steps are used to achieve portfolio management:

First, determine the securities investment policy. Different investors will adopt different investment policies because of their different investment styles. To formulate an investment policy is to determine the investment goal, the scale of investment and the object of investment. Determine the investment goal is to determine the risks and benefits of investment projects (Xia et al., 2014). The total amount of money used to invest is to determine the size of the investment. Determining the object of the investment is to determine the risk assets to be invested, such as several securities. Different investment objectives of investment projects, the choice of investment targets are different.

Secondly, securities investment and analysis are necessary. The goal of this step is to find securities priced at the wrong price on the basis of the first step of the investment target. The main method used is to analyze the factors that influence the fluctuation of the securities price and the mechanism of the formation of the securities price.

Thirdly, the portfolio is constructed. The main task of this step is to determine the proportion of securities and their investments.

Then, complete the amendment to the portfolio. The purpose of this step is to update the portfolio to fit the dynamics of the market. The market is changing and must be adjusted to fit the current market. However, any adjustment has to pay the transaction costs, and it should stand in the overall perspective. Individual adjustments are made within a range to improve the risk return of the existing portfolio.

Finally, evaluate portfolio performance. The purpose of this step is to accumulate experience, which is a feedback of performance and result of portfolio management.

3.3 A mathematical model of securities investment

Securities investment is a multi-objective, multi-stage, multi constrained nonlinear optimization problem. According to the investment objectives and constraints, the objective function is established：

$$\min W = P + T. \tag{5}$$

In the formula (5): W is the loss of the securities investment company after the failure occurs; P is the system network loss; T is the switching operation cost.

In addition to ensuring that users can restore the power supply in time and reduce the loss of protection benefits, the network loss after the recovery of the security investment is still the smallest in the network structure after recovery. To minimize the losses suffered by securities investment companies after failures, and to protect the interests of securities investment companies. Therefore, the net loss of the securities investment should be minimized after the restoration of the network：

$$P_{\text{loss}} = \sum_{i=1}^{N} K_i R_i \frac{P_i^2 + Q_i^2}{U_i^2}. \tag{6}$$

$$S_i \le S_{i,\max}; \tag{7}$$

$$U_{i,\min} \le U_i \le U_{i,\max} \tag{8}$$

In the formula (6): P_{loss} is the securities investment losses; N is the number of branches of securities investment; R_i is the branch of the branch resistance; P_i、Q_i is the branch active power and reactive power; U_i is the node voltage at the end of the branch; K_i is a state variable branch switch ;S_i、$S_{i,\max}$ is the power; and passing through the branches of the calculated values and the maximum allowable value; $U_{i,\min}$、$U_{i,\max}$ is the node of the upper and lower voltage value.

The switch in the securities investment is divided into two kinds according to the running situation: the sectional switch and the connection switch. As the power supply is restored, the life of the equipment will be affected by the operation. Therefore, each fault recovery should be operated as little as possible to minimize the loss, so the loss of switch wear is added to the objective function：

$$T_{\text{a}} = K_{\text{sec}} \sum_{i=1}^{m} S_{\text{sec},i} + K_{\text{con}} \sum_{j=1}^{n} S_{\text{con},j}. \tag{9}$$

In the formula(9): T_{a} is switch wear loss; $S_{\text{sec},i}$ is switches, and the action mark is 1; $S_{\text{con},j}$ is the focal switch, and the action mark is 1; and for each action a switch to formula plus 1; m and n are in accordance with the feeder terminal unit (FTU) section to get the statistics of each section switch number; K_{sec}、K_{con} is the loss of the conversion coefficient of sectionalizing switches and tie switch, switch type and type according to the corresponding parameter settings.

In order to establish a unified measurement model, these indexes can be converted into loss index in accordance with their respective conversion relation.

4. APPLICATION OF ANT COLONY ALGORITHM IN SECURITIES INVESTMENT

In the reconstruction of securities investment, the losses on each branch will change as the whole network shape changes. The weights of each edge are constantly changing, and it is not enough to build a tree with minimum weight. The minimum weight of the securities investment network often can not meet other constraints, such as equipment capacity constraints, voltage drop constraints. The ant colony algorithm is introduced here, and the algorithm can learn the weights of each edge. It reflects the degree to which the side is selected, that is to say, the influence of the selected side on the network reliability. The algorithm is constantly evaluated according to the proposed scheme, and then the self-knowledge is constantly revised.

Ant colony algorithm (ACO) is a learning algorithm with positive feedback. It can constantly revise its knowledge through learning. The ants communicate with each other through pheromones, and constantly adjust the amount of pheromones on each side so as to achieve the purpose of learning. The ant colony algorithm search strategy is given in the form of a probabilistic search algorithm in the direction of choice, more likely towards better solution domain has been found, while the other direction may also be selected, so the algorithm is easy to fall into local optimal. At the t moment, the antk selects from the set which side is determined by the transformation probability, and the probability that the ant k in the node b chooses to move to the node c is:

$$p_{bc}^{k}(t) = \begin{cases} \dfrac{\tau_{bc}^{\alpha}(t)\eta_{bc}^{\beta}(t)}{\sum_{d \in F_t^k} \tau_{bd}^{\alpha}(t)\eta_{bd}^{\beta}(t)}, c \in F_t^k; \\ 0, \qquad c \notin F_t^k. \end{cases} \tag{10}$$

Where: $F_t^k = \{0,1,...\}$ is the set of feasible paths for the ant k; $\tau_{bc}^{a}(t)$ is the amount of information on the edge of (b,c); η_{bc} is the visibility of the edge (b,c); α and β are two parameters, respectively, reflecting the ants in the movement of the accumulated information and inspiration information in the ant selection path of the relative importance of the more pheromone more easily selected.

The total flow chart of the ant colony algorithm is shown in figure 1 below

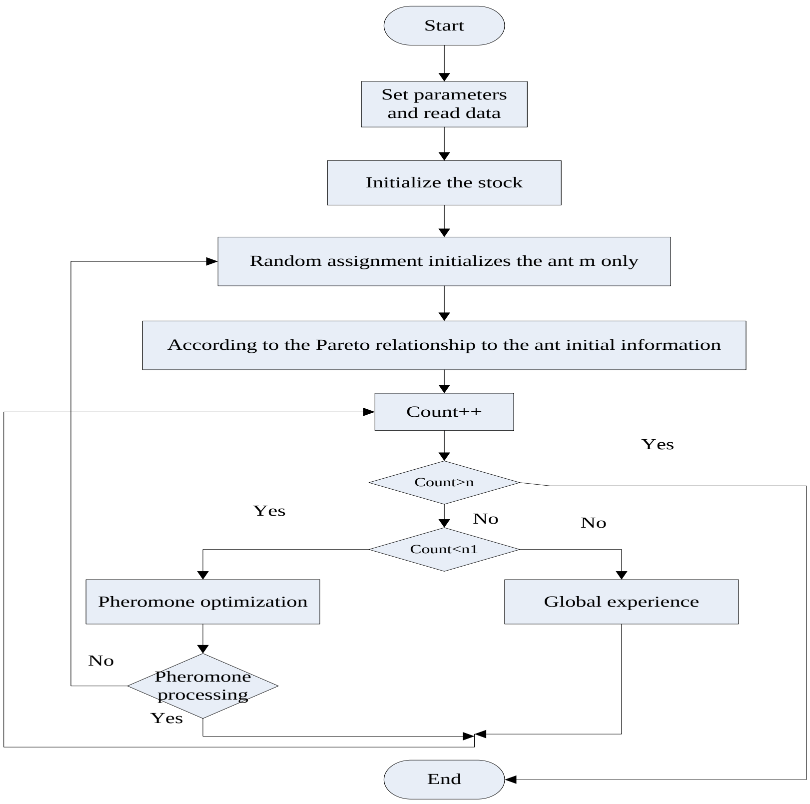


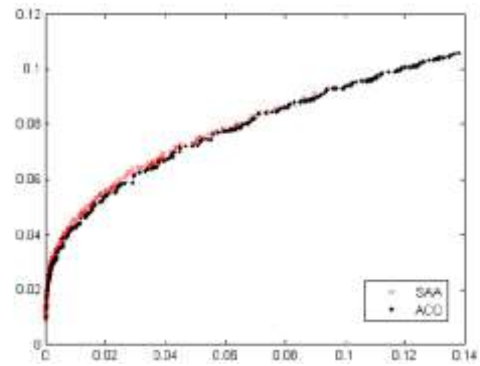
Figure 1. Total flow chart of ant colony algorithm

Where n1 represents the number of times based on the transition probability, and n represents the total number of cycles, then (n-n1) is the number of times based on the niche optimization. m represents the size of the ant colony. Count is the counter, used to record the current number of iterations, the initial value of 0.

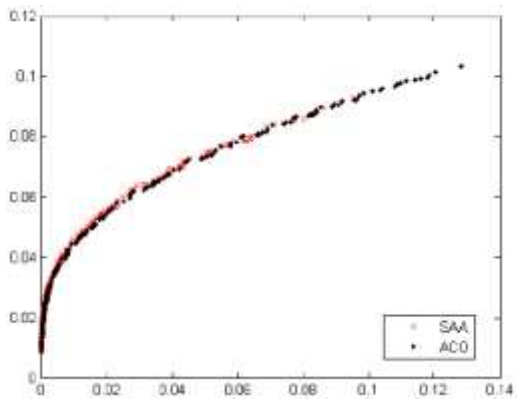
The pheromone concentration τ_{ij} is used to guide ant cooperative optimization through positive feedback mechanism, and the positive feedback effect of pheromone concentration τ_{ij} on the search is determined by the information heuristic factor alpha. The higher the value of α, the higher the influence of pheromone. At this point, ants tend to choose the path chosen by most ants, which makes the collaboration between ants increase, but at the same time reduces the randomness of search. When the value of α is smaller, the influence of pheromone on search is lower. At this point, the ant search is more dependent on heuristic information.

The expected heuristic factor β reflects the impact of heuristic information on the search. The greater the value of β, the greater the influence degree of the heuristic information. The ant is more inclined to choose the local optimal solution, which makes the algorithm converge faster, but easy to fall into the local optimum. This paper uses the update strategy of adaptive information, specific use of each pheromone update value is K times the value of the heuristic function method, the pheromone concentration updating values with solution quality change.

The following figure 2 is a comparison graph of ant colony algorithm (ACO) and simulated annealing (SAA). The abscissa represents the combination risk, and the ordinate represents the combined revenue. The figure (a) is the same number of iterations, and the figure (b) is the result of changing the parameter.



(a) Comparison chart of the same iteration number



(b) Result map for changing parameters

Figure 2. Comparison charts of ACO and SAA

4. CONCLUSIONS

Based on the multi - objective optimization method, this paper studies the securities portfolio problem, taking into account the two factors of revenue and risk, using the improved ant colony algorithm to find the Pareto frontier. This paper is a research and attempt on the use of ant colony algorithm in multi - objective optimization of portfolio investment. Specifically, the classic TSP ant colony algorithm modeling has been improved, such as the ant and the pheromone retention method; Pareto relationship to determine and judge. In the aspect of algorithm improvement, adaptive pheromone updating strategy and maximum and minimum pheromone are adopted to prevent the algorithm from falling into local optimum. The initial use of the algorithm is based on the transition probability of the basic ant colony algorithm optimization, later in the existing Pareto solution based on the use of niche technology to search, increase the diversity of solution set. Finally, the article makes a simple analysis of the parameters, which clarifies the effect of parameters and the influence on the performance of the algorithm.

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