Research of Improved Artificial Fish Swarm Portfolio Optimization Algorithm Based on Adaptive Levy Mutation

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Abstract

With the rapid development of the economy, the stock market is growing like mushrooms, and a large number of enterprises and individuals invest in all kinds of securities. In the stock market, the investment itself with a certain risk, some assets have high risk, and some assets with low risk, investors must choose which securities products to makes higher income, it is particularly important for different investors. It has become very important to choose the investment plan reasonably so that investors can get the highest return on acceptable risk level, which has become the focus of many scholars. The research of portfolio theory has a very important influence on the stock market. In the process of investment market, we select appropriate proportion of investment so that reduce the risk of investment, and access to greater income. At present, most of the intelligent optimization algorithms could be used to optimize the investment portfolio model. In view of the basic artificial fish swarm algorithm is easy to fall into local extreme value and the search speed is slow, this paper combine basic artificial fish swarm algorithm with Levy mutation. Computer simulation shows the improved algorithm has better convergent performance, And this paper takes the stock exchange price data of five stocks in Shanghai stock exchange for 100 days as an example. The improved algorithm is used to solve the investment portfolio model. Experimental results show that the income is increased, and the risk is reduced.

Keywords: Levy mutation, Artificial fish swarm, Portfolio model, Transaction cost

1 Introduction

In 2002, artificial fish swarm algorithm was proposed by Li et al. [1] firstly. This is a kind of heuristic artificial intelligence algorithm. The algorithm mainly adopt the serial or parallel mode in implementing cluster, collision, foraging and random behaviors of fish swarm, which is a generalized neighborhood search algorithm and good at searching the global. With the continuous research of artificial fish swarm algorithm, it is found that the convergence precision of the algorithm is limited, convergence rate is slow and easy to fall into local extreme value which is insufficiently [2].

Recently, faced with the shortage of artificial fish swarm algorithm, many scholars have advanced lots of improved algorithms. Most of them proposed combine the artificial fish swarm algorithm with other algorithms. Li and Liu [3], facing defects such as more blind, slow speed in the latter convergence of the algorithm, they did some analysis on fish swarm to imitate the social division, cooperation and competition. Through developing a number of artificial fish swarm to search with multi-swarm and multi-strategy at the same time, the searching efficiency and speed of the algorithm are greatly improved. Yao et al. [4] used the global convergence of the artificial fish swarm algorithm to get a small range of solution.

Particle swarm optimization algorithm is used for local search, which has better convergence accuracy. Liang and Pei [5] presented using particle swarm optimize basic artificial fish swarm algorithm, and introduced information strategy, local fast convergence, particle velocity. The optimization accuracy of the improved algorithm is improved. Fei et al. [6] proposed the method of DNA cross mutation to improve the convergence precision and speed. Zhao et al. [7] used flexible parameter settings so that produce a positive effect on searching ability and speed in the late period of algorithm search. Fu [8] improved initialization of the artificial fish swarm algorithm by using the probability density function, which effectively avoided the weakness of initialization disorder. In the foraging behavior and chaotic, algorithm is adopted to reduce the time to obtain the local optimal solution and the better convergence results. Ji et al. [9] introduced the swallowed and jump behavior, which effectively improved the performance of the algorithm, and the improved algorithm is applied to job scheduling. Huang et al. [10] proposed artificial fish swarm algorithm combined with greedy fish,

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DOI: 10.3966/160792642019102006019

which required to execute the foraging behavior to search around the optimal artificial fish. The improved algorithm has fast convergence speed and good accuracy. Fei et al. [11] combined bacterial foraging algorithm with artificial fish swarm algorithm, and used chemotaxis to help improve the convergence performance of artificial fish swarm algorithm.

Since Markowitz proposed the portfolio model in the securities market firstly, portfolio model quantified the investment market returns and risks, and sped up the research on the investment market. At present, there are a lot of investment portfolio models with constraints such as the combined model of absolute deviation risk, the combined model based on fuzzy theory and the dynamic portfolio model, etc. With the rapid development of computer technology, more and more researchers used artificial intelligence algorithms to optimize the portfolio model. Ma et al. [12] adopted double target non dominated sorting theory to strengthen the search capability of basic artificial fish swarm algorithm, and used the improved algorithm to solve the foreign exchange portfolio model. Xia et al. [13] proposed a combination model with transaction costs, and took advantage of the particle swarm optimization algorithm to optimize the model. Qi et al. [14] proposed three kinds of transaction costs of the portfolio model, then used genetic algorithms and parameters with two planning method to optimize the solution of the three models.

In this paper, a new improved artificial fish swarm algorithm is proposed, which combines the Levy mutation with the artificial fish swarm algorithm to avoid falling into local extreme value and improve the convergence precision of the algorithm. The optimization speed is improved by using the adaptive field of view and the step size. And the improved algorithm is used to optimize the investment portfolio model with transaction costs. Compared with the basic fish swarm algorithm, the income is increased and the risk is reduced.

2 Portfolio model with transaction costs

First of all, if investors are holding the capital K and preparing to invest into market with n kind of risk assets (that is $\mathrm{A}_i\left(i=1,2\cdots,n\right)$). In order to simplify the calculation process, the variables used in the combined model are described as follows [15]:

$\mathrm{a_i}$ is the proportion of i asset in total assets, and the sum is 1; R_i is the return of i asset during a period of investment; S_i is the risk rate of i assets in a certain period of investment; C_i is the transaction cost ratio of i asset in a certain period of investment; Π_i is the transaction cost of i asset in a period of investment.

In this paper, the transaction cost of the combined model is defined as follows: When the amount of investment is less than a fixed value (Γ_i), the transaction cost is $\Gamma_i C_i\left(i=1,2,\cdots,n\right)$; When the investment amount exceeds the fixed value (Γ_i), the combined transaction cost is $\mathrm{K}a_i C_i\left(i=1,2,\cdots,n\right)$.

In a certain period of investment, the total investment income is $\sum_{i=1}^{n}\mathrm{K}a_i R_i$; The total risk is the minimum value of all assets risk, that is $\min\left[\mathrm{K}a_i S_i\right]$, Adopting the opposite number in each of the brackets is equivalent to $-\max\left[\mathrm{K}a_i S_i\right]$; The goal of the portfolio model is to maximum the revenue and minimize the risk at the same time. Due to the different degree of preference for different investors, therefore, this paper uses the weight coefficient $\delta\left(0<\delta<1\right)$ to control the relationship between income and risk in the portfolio model, thus obtains the single objective investment combined problem, namely the model is

$$\max F\left(a\right)=\delta\sum_{i=1}^{n}\left(\mathrm{K}a_i R_i-\Pi_i\right)+\left(1-\delta\right)\left\{\max_{1\le i\le n}\left\{\mathrm{K}a_i S_i\right\}\right\}$$
$$s.t.\sum_{i=1}^{n}a_i=1;0\le a_i\le 1;0<\delta<1 \quad \mathbf{(1)}$$

Among them, in the limit of $\delta\to 0$, that is to say investor is more cautious; In the limit of $\delta\to 1$, that is to say investor prefer adventure.

3 Basic Artificial Fish Swarm Algorithm

Artificial fish swarm algorithm is a simulation of natural fish behavior (including cluster, following, foraging and random behavior), and choose one of behaviors to be executed. Each artificial fish obtains its own local optimal solution and then sends the information to the fish swarm system so that obtain the global optimal solution [16].

Algorithm involves variables as follows: suppose there is n artificial fishes, current status of artificial fish is $\mathrm{X}=\left(x_1,x_2,\cdots,x_n\right)$, the $x_i\left(i=1,2\cdots,n\right)$ is the spatial position component of artificial fish; Search radius of artificial fish is *visual* ; Artificial fishes are able to move the distance is *step* each iteration; Optimization objective function value is $\mathrm{Y}=f\left(\mathrm{X}\right)$, namely food concentration in the position of the artificial fish swarm; The distance between the i and j artificial fish is $d_{ij}=\left|\mathrm{X}_i-\mathrm{X}_j\right|$.

(1) Cluster behavior. In order to betterly adapt to the environment needs, fish swarm generally tend to be close to partners, while maintaining a certain distance(namely congestion degree is ω). The current artificial fish state is X_i, so it is $\mathrm{Y}_i=f\left(\mathrm{X}_i\right)$. There is n_t fishes near it, and the center of the fishes is X_a, so

$Y_a = f(X_a)$. If $Y_a / n_t > \omega Y_i$, then artificial fish execute cluster behavior to the direction of X_b as follows,

$$X_b = X_i + \frac{X_a - X_i}{\|X_a - X_i\|} \cdot step \cdot rand() \quad \textbf{(2)}$$

(2) Following behavior. When fish swarm are searching for food, they often follow around the fishes that have found food, noting the current artificial fish is X_i, then $Y_i = f(X_i)$. There is n_t fishes near it, and the best states of the fishes is X_e, so $Y_e = f(X_e)$. If $Y_e / n_t > \omega Y_i$, artificial fish execute following behavior to the direction of X_k,

$$X_k = X_i + \frac{X_e - X_i}{\|X_e - X_i\|} \cdot step \cdot rand() \quad \textbf{(3)}$$

(3) Foraging behavior. Artificial fish generally perceive the food concentration in the surrounding neighborhood by visual perception, and choose whether to tend to the goal. Suppose this paper is seeking the maximum value, the current artificial fish state is X_i, then $Y_i = f(X_i)$. Choosing an artificial fish around the neighborhood of X_i, and recorded as X_j, so $Y_j = f(X_j)$. If $Y_j > Y_i$, then artificial fish execute foraging behavior to the direction of X_k as follows,

$$X_k = X_i + \frac{X_j - X_i}{\|X_j - X_i\|} \cdot step \cdot rand() \quad \textbf{(4)}$$

(4) Random behavior. It is a behavior in larger range of searching partners or food, which belongs to the supplement of the foraging behavior.

(5) Bulletin board. Algorithm takes the current optimal fish and its function value into the bulletin board (that is temporary variable). The artificial fish swarm obtain the optimal artificial fish and its function value each iteration, which is compared with the billboard board, and selecting the best to update bulletin board.

4 Improved Artificial Fish Swarm Algorithm

4.1 Main Idea

Artificial fish swarm algorithm has strong global search ability and parallel searching behavior. But there are some shortcomings such as slow convergence, easily fall into local extremum and so on, which are particularly prominent when solving the problem with more local extremum points.

Therefore, in this paper, the Levy mutation is used to optimize the artificial fish swarm algorithm so that it can jump out of the trap so that get the global optimal value when the artificial fish fall into the local extremum. The method of adaptive visual field and step is adopted to make the visual field of early search large and the visual field of later convergence is small at the same time. The improved algorithm has stronger global search ability, and the optimal value can be obtained more quickly.

4.2 Introduce Mutation

Levy mutation is based on the Levy distribution. The artificial fishes are divided into two categories. One kind has better optimization results, and the other is relatively poor. When the mutation probability is less than the threshold, fishes with poor optimization execute Levy mutation, then fishes can jump out of the local extreme value so that avoid falling into trap. The so-called Levy mutation, that is to improve the status of artificial fish by mutation. Levy mutation by formula (5). This paper use the formula (6) to generate a random number that obey Levy distribution, and add the random number to the original fish so that generate new individual, which will get better optimization results.

Suppose the artificial fish swarm has n fishes. For each of the artificial fish X_i, this paper set it as a vector with two components, namely $X_i = (x_i, \eta_i)$, and use it to represent the father's generation. $X_i' = (x_i', \eta_i')$ is regard as the offspring produced by the mutation. The mutation process is as follows [17]:

$$\begin{cases} \eta_i'(j) = \eta_i(j) e^{\left[\tau N(0,1) + \tau' N_j(0,1)\right]} \\ x_i'(j) = x_i(j) + \eta_i'(j) \Phi_j(0,1) \end{cases} \quad \textbf{(5)}$$

Among them, $j = 1, 2, \cdots, u$, u represent space dimension of artificial fish, namely $x(j)$ is the number j of components in the solution vector, $\eta(j)$ is the number j of components of variance; i represent individual sequence of artificial fish. $N(0,1)$ stands for random number that generated by Gauss distribution (mean value is 0, standard deviation is 1); $N_j(0,1)$ stands for random number of the j component. τ and τ' are set to be $\left(\sqrt{2\sqrt{u}}\right)^{-1}$ and $\left(\sqrt{2u}\right)^{-1}$ respectively. $\Phi_j(0,1)$ stands for random number of the j component, which generated by the Levy distribution.

Levy probability distribution as follows:

$$\phi_\alpha(y) = \frac{1}{\pi}\int_0^\infty e^{-q^\alpha}\cos(qy)\,dq, \quad y \in R \tag{6}$$

As can be easily seen from Eq. (6), this distribution has an important parameter α ($0 < \alpha < 2$). It controls the shape of the distribution function, and the different parameter α present different distribution. For example, if α =1, Levy distribution approaches Cauchy distribution; When α tends to 2, Levy distribution is closer to Gauss distribution. The parameter α in this paper satisfies $0.8 < \alpha < 1.95$.

4.3 Adaptive Visual Field and Step Size

The basic ideas of adaptive visual field and step size: In the initial stage of optimization, due to the distributed of artificial fishes are in the entire definition domain, the visual field and the step size should be larger; In the late stage of convergence, the artificial fishes gathered in the vicinity of the optimal value, and we should adopt a smaller visual field and step size. Faced with cluster, following, foraging and random behavior, this paper adopt adaptive adjustment of visual field and step size to make the vision and step along with the changing of the iteration. The average distance between the current artificial fish and other artificial fish are calculated each iteration, which recorded as *Visual* 1. Using coefficient ξ (in which $\xi \in (0,1)$) to get the step size, that is $step1 = \xi * visual1$, which is regard as the visual field and step size of cluster and following behaviors [18].

Then the visual field and the step size of foraging behavior that include its default random behaviors are set up: The distance between the current artificial fish and the optimal fish is regard as *Visual* 2; The distance between the current artificial fish and the nearest individual fish in its neighborhood is regard as *Visual* 3. The corresponding steps are $step2 = \xi * visual2$ and $step3 = \xi * visual3$ respectively. Regarding *Visual* 2 and *Visual* 3 as the visual field respectively to perform the search so that obtain two optimal fish, and take the better one, then advance to its direction with the corresponding step size.

4.4 Execution Steps of Improved Algorithm

(1) Randomly generating the initial artificial fish swarm, it includes the number of fish swarm, the number of search times, the visual field, step size and so on;

(2) For each artificial fish, calculating the objective function value so that get the best and update bulletin board, which includes the optimal position and function value of artificial fish;

(3) Through calculating visual field and step size, the artificial fish choose the corresponding visual field and step size to execute fish behaviors that contain cluster, following, foraging and random behaviors;

(4) Judging whether meet the conditions of variation (that is the change of two bulletin board value is less than the variation threshold value), If satisfied, the current state of the poor individual fish execute mutation operation, otherwise the iteration increases, and go to the next step;

(5) Judging whether the iteration is accomplished, if it is, the algorithm stops, otherwise, return to step (2).

5 Algorithm Simulation

This paper adopt five classical test functions [19] of algorithm to test the performance of the improved artificial fish swarm algorithm by MATLAB.

(1) $\min f(x,y) = x^2 + y^2 - 10(\cos 2x + \cos 2y) + 20$, Where $-5.12 \le x, y \le 5.12$;

(2) $\min f(x,y) = (x^2 + y^2)^{0.25}\left\{\sin^2\left[50(x^2+y^2)^{0.1}\right]+1\right\}$, Where $-100 \le x, y \le 100$;

(3) $\min f(x,y) = -\left[\sum_{i=1}^{5} i\cdot\cos((i+1)x+i)\right]\times\left[\sum_{i=1}^{5} i\cdot\cos((i+1)y+i)\right]$, Where $-10 \le x, y \le 10$;

(4) $\max f(x,y) = \frac{\sin(x)}{x}\frac{\sin(y)}{y}$, Where $-1 < x, y < 2$;

(5) $\min f(x,y) = \frac{1}{4000}(x^2+y^2) - \cos x \cos\frac{y}{\sqrt{2}} + 1$, Where $-600 \le x, y \le 600$;

We get the three-dimensional cubic diagram of these test functions by MATLAB, respectively as follows Figure 1 to Figure 5.

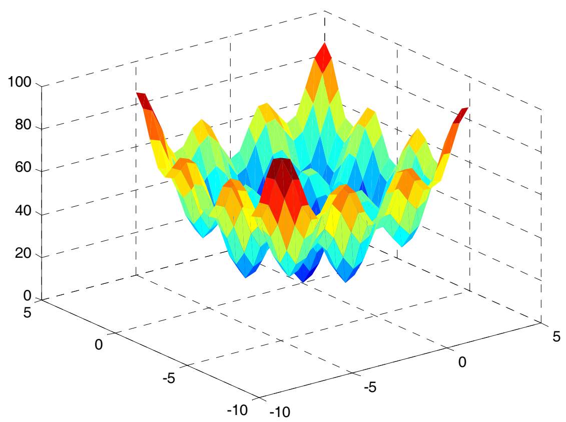

Figure 1. Cubic diagram of test function 1

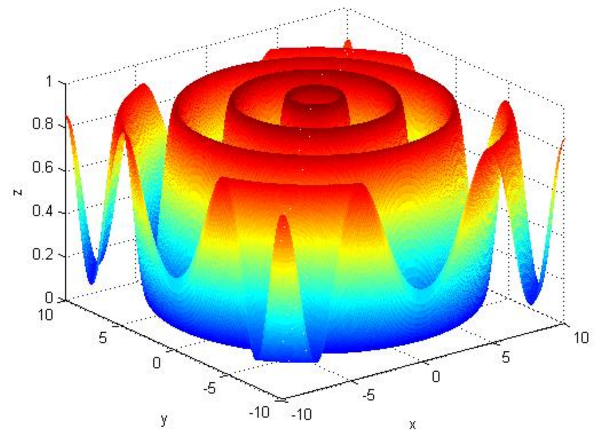

Figure 2. Cubic diagram of test function 2

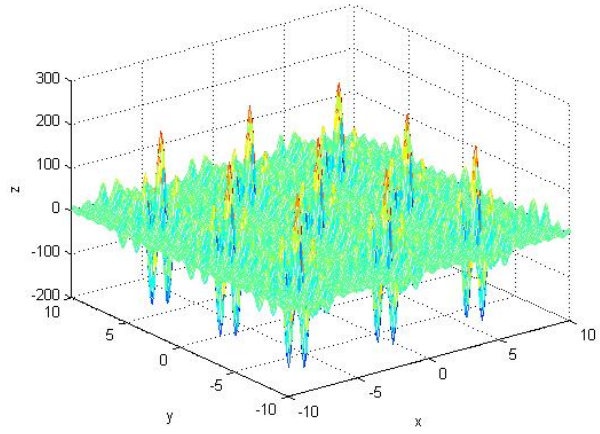

Figure 3. Cubic diagram of test function 3

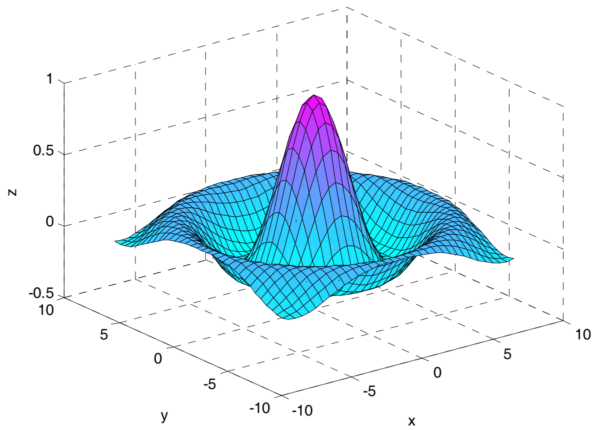

Figure 4. Cubic diagram of test function 4

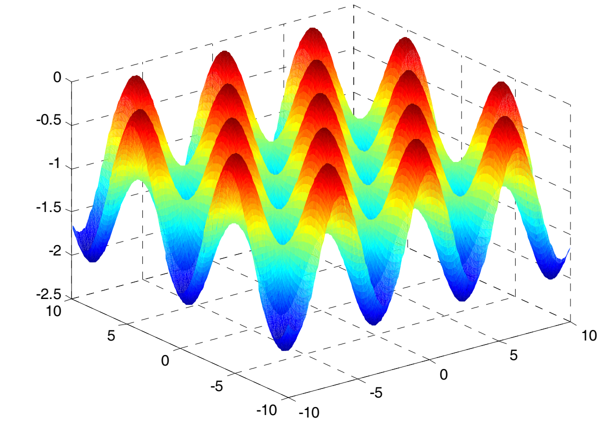

Figure 5. Cubic diagram of test function 5

The following are the parameters that have been used in the experiments: The number of fish swarm is $fishnum = 100$; Visual field is $visual = 2.5$; Step size is $step = 0.4$; number of iterations is $\max gen = 100$; congestion degree is $\omega = 0.618$; The parameter $\xi = 0.5$; Mutation probability (i.e. variation threshold) $p = 0.001$. This paper use the basic artificial fish swarm algorithm (i.e. AFSA) and the improved artificial fish swarm algorithm (i.e. IAFSA) to execute simulation experiment 30 times with five functions above. The average number of iteration times of convergence is regarded as average convergence times. The number of experiments that achieve the accuracy of the target occupy the total experiment is regarded as the success rate. The results of the experiment are shown in Table 1 (the accuracy is 0.000001).

Table 1. test results

	test result 1		test result 2		test result 3		test result 4		test result 5	
	AFSA	IAFSA	AFSA	IAFSA	AFSA	IAFSA	AFSA	IAFSA	AFSA	IAFSA
Optimal solution	0.000026	0.000000	2.583065	0.000699	186.700458	186.730909	0.999999	1.000000	0.107999	0.000153
Worst solution	0.000567	0.000001	3.176905	0.002624	185.890706	186.730908	0.999994	1.000000	0.421915	0.001712
Average value	0.000297	5E-7	2.879985	0.001662	186.295582	186.730909	0.999997	1.000000	0.264957	0.0009325
Average convergence Iteration number	95	23	61	47	20	15	21	7	52	48
Success rate (%)	75	94	30	98	77	99	68	100	34	85

As can be seen from Table 1, in terms of performance, the improved artificial fish swarm algorithm (i.e. IAFSA) compared with the basic artificial fish swarm algorithm (i.e. AFSA) has been greatly improved. Even if the search area of test function is larger or has more local extreme value, IAFSA can jump out of local extreme value, and get the global optimum. The convergence speed significantly accelerated, and the success rate of convergence is obviously improved.

Figure 6 to Figure 10 is the optimization process curve of test functions 1-5 respectively.

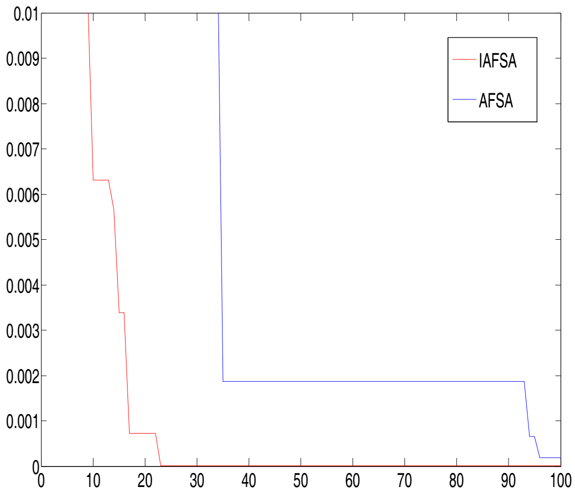

Figure 6. The optimal path curve of function 1

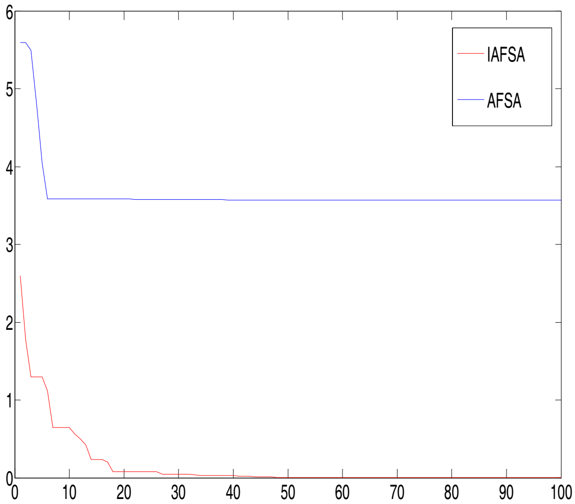

Figure 7. The optimal path curve of function 2

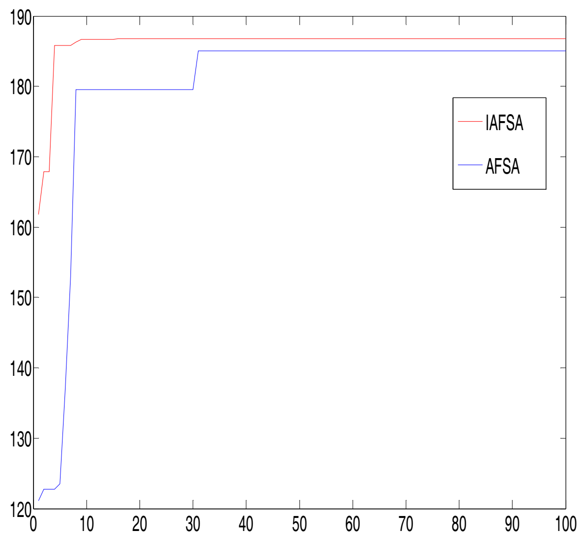

Figure 8. The optimal path curve of function 3

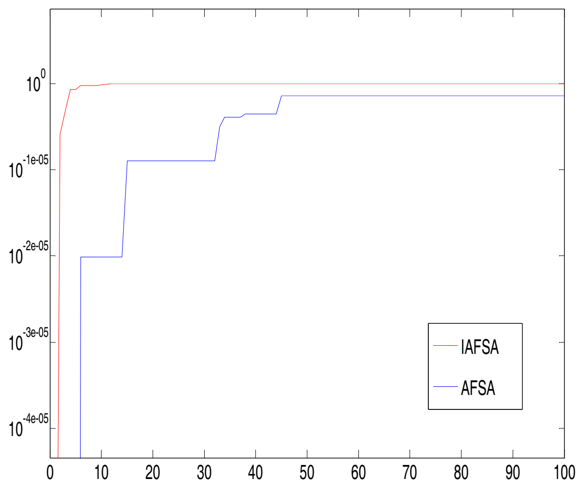

Figure 9. The optimal path curve of function 4

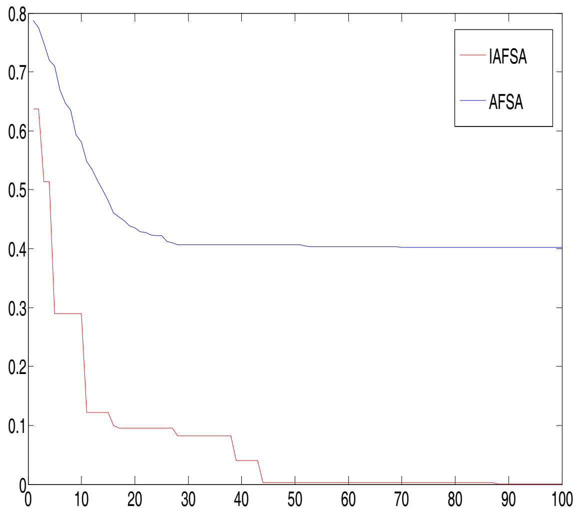

Figure 10. The optimal path curve of function 5

From the five functions of the optimization curve, the improved artificial fish swarm algorithm has good results in the optimization of the target accuracy, speed, etc.

6 Optimization of Portfolio Model Based on Improved Algorithm

6.1 The Penalty Function is Added to the Model

In general, the penalty function method is used to solve the objective function with constraints. The core is that form different constraints into proper penalty function, and the penalty factor is added to the original objective function so that obtain the unconstrained single objective augmented function [20].

According to the constraints of the model, the combination model is simplified by the exterior point penalty function, and the points in the process are divided into two types. One is in the constraints, the other is outside that will be punished. In the process of optimization, the parameter γ becomes large continuously. At the end of the iteration, the search point is in the constraints, which is the target solution. Then, the portfolio problem model is changed as follows:

$$\max F(a) = \delta \sum_{i=1}^{n} \left(\mathrm{K} a_i R_i - \Pi_i \right) + (1-\delta) \left\{ \max_{1 \le i \le n} \left\{ \mathrm{K} a_i S_i \right\} \right\}, \\ -\gamma \left(\sum_{i=1}^{n} a_i - 1 \right)$$

where $\gamma = 7^k \left(k = 1, 2, \cdots \right)$. **(7)**

6.2 The Steps to Solve the Combination Problem

(1) Randomly generating the initial artificial fish swarm, it includes the number of fish swarm, the number of search times, the visual field, step size, etc;

(2) The objective function is constructed by the combined model, besides, the outer point penalty function method is used to transform the problem into an equivalent unconstrained problem;

(3) For each artificial fish, calculating the objective function value so that get the best to update bulletin board, which includes the optimal position and function value of artificial fish;

(4) Through calculating visual field and step size, the artificial fish choose the corresponding visual field and step size to execute behaviors that contain cluster, following, foraging and random;

(5) Judging whether meet the conditions of variation (that is the change of two bulletin board value is less than the variation threshold value), If satisfied, the current fish which is being poor state execute mutation operation, otherwise the iteration increases, and go to the next step;

(6) Judging whether the iteration is accomplished, if it is, the algorithm stops, otherwise, return to step (3).

The flow chart of the solution is shown in Figure 11.

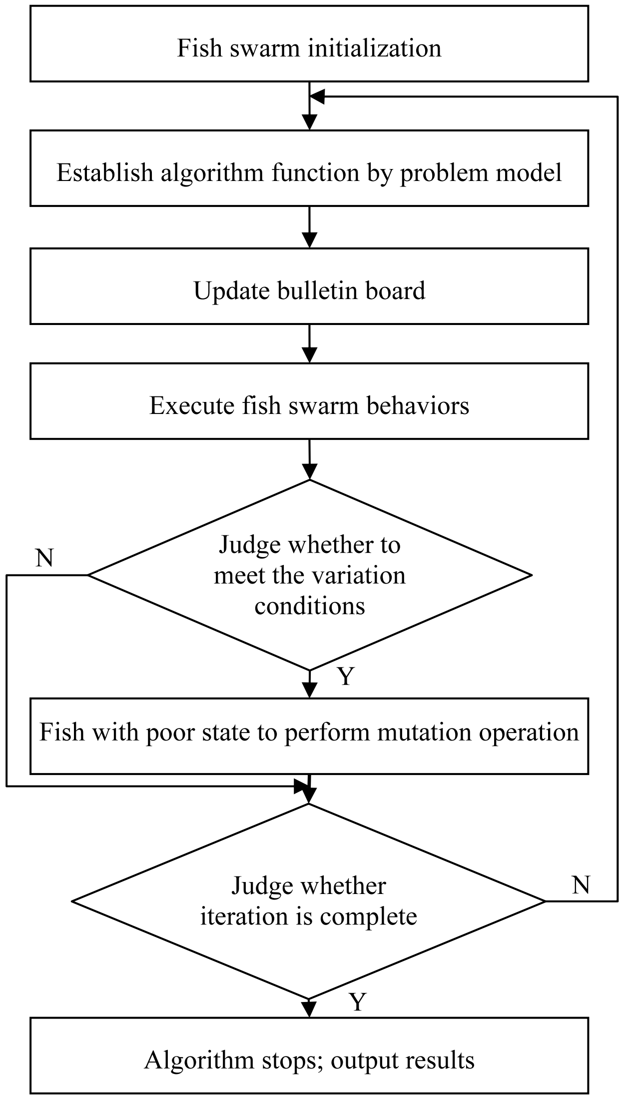

Figure 11. Flow chart of solution

6.3 Improved Algorithm for Solving Model

In this paper, the data is based on the Shanghai stock exchange, selecting the stock day opening - closing price data from November 17, 2014 to April 16, 2015, and a total of 100 days of stock price data. The selected stocks are ICBC, CRCC, Petro China, CSCEC, Bank of China, a total of five stocks. Setting P_{it} as the closing price of i stock at t time, P_{it+1} expresses the closing price of i stock at $\mathrm{t}+1$ time, and calculate the return rate of i stock on day t on the basis of the closing price of each stock at the day of t and the closing price of the next day, to be remembered as $\mathrm{R}_{\mathrm{it}} = \frac{\mathrm{P}_{it+1} - \mathrm{P}_{it}}{\mathrm{P}_{it}}$, ($\mathrm{i}=1,\cdots,5$, $\mathrm{t}=1,\cdots,100$) [21]. By calculating the yield of five stocks in 100 days, the average yield of each stock can be viewed as $\mathrm{R}_{\mathrm{i}} = \frac{1}{100} \sum_{t=1}^{100} \mathrm{R}_{it}$. It is used as the empirical yield of this article. According to the yield data of each stock for 100 days, the variance formula of each stock change is calculated directly according to the variance formula, and the standard deviation is obtained at the same time as the risk of the stock. By finding the provisions of the Shanghai stock exchange for the cost of the stock exchange C_i, the specific transaction cost rate of different stocks and the critical value of the transaction cost are calculated Γ_i. Specific data such as Table 2.

Table 2. Portfolio model data

	R_i	S_i	C_i	Γ_i
ICBC	0.004397	0.027585	0.0487	100
CRCC	0.011508	0.044711	0.0487	100
Petro China	0.005516	0.031463	0.0487	100
CSCEC	0.008152	0.036395	0.0487	100
Bank of China	0.005122	0.032393	0.0487	100

The parameters that be used in the experiments as follows: The number of fish swarm is $fishnum = 100$; visual field is $visual = 2.5$; step size is $step = 0.4$; iteration number is $\max gen = 100$; congestion degree is $\omega = 0.618$; the parameter $\xi = 0.5$; mutation probability (i.e. variation threshold) $p = 0.001$.

The selection of different parameter δ, which has a greater influence on solving the combination problem. In this paper, we select three values that contain 0.1, 0.3, 0.5, and use the improved algorithm (i.e. IAFSA) and basic fish swarm algorithm (i.e. AFSA) to optimize the model. The results are shown in Table 3.

Table 3. The comparison results of solving the portfolio model

Weight	Method	x_1	x_2	x_3	x_4	x_5	R (%)	S (%)	F (x)
δ =0.1	AFSA	0.0000	0.9775	0.0173	0.0108	0.0254	18.4800	5.3760	46.1939
	IAFSA	0.0000	0.0000	1.0000	0.0000	0.0000	19.0000	1.5002	73.4399
δ =0.3	AFSA	0.0352	0.1246	0.6308	0.2654	0.0000	16.5000	1.5000	39.9326
	IAFSA	0.0000	1.0000	0.0000	0.0000	0.0000	18.5000	1.4801	48.7699
δ =0.5	AFSA	0.0036	0.0815	0.8006	0.0523	0.0644	18.1718	1.4200	57.0109
	IAFSA	0.0000	0.0000	1.0000	0.0000	0.0000	19.0000	1.4200	74.0050

Table 3 shows the obvious comparison results of different algorithm. When the parameter δ adopts 0.1, 0.3 and 0.5 respectively, the improved algorithm (IAFSA) has shown a more obvious optimization performance. The investment income increases effectively, while the assets risk is further reduced, and the target function value of the model increases correspondingly. For example, if $\delta = 0.3$, revenue R increases by 12.1212%, while the risk S is reduced by 1.3267%, and the objective function value increases by 22.1305%.

From the process of solving the problem of combination curve can be more intuitive to see that the improved algorithm has a strong ability to optimize, as shown in Figure12 to Figure 14. The meaning of x-axis and y-axis are Number of iterations and optimal value.

In summary, the improved algorithm has better effect on solving the portfolio model.

7 Conclusion

In view of the shortcomings of the basic artificial fish swarm algorithm, such as easily falling into local extremum, slow search speed and so on, this paper puts forward a new idea of improvement, which combines the Levy mutation with the artificial fish swarm algorithm so that improve the convergence precision of the algorithm. Besides, the average visual field and step size are used to the cluster and following behavior, while the foraging behavior adopt adaptive visual field and step size that contains optimal and recent distance of artificial fish. The results of solving five classical test functions show that the improved algorithm has better optimization performance. With the continuous development of the economy, the trend of globalization is becoming more and more obvious, the market competition is more intense, and the development of the market is also affected by many unpredictable factors. Therefore, how to choose investment strategies to get more benefits is a hot topic at present. This paper

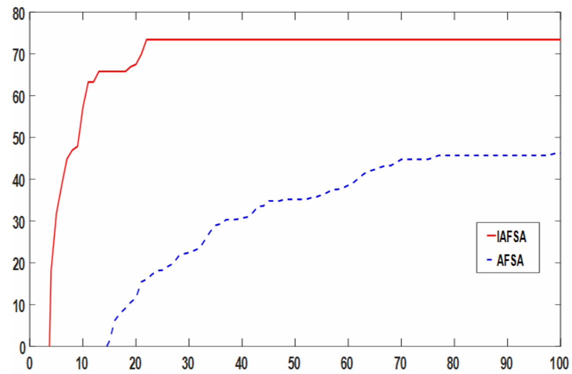

Figure 12. Optimized contrast chart when $\delta = 0.1$

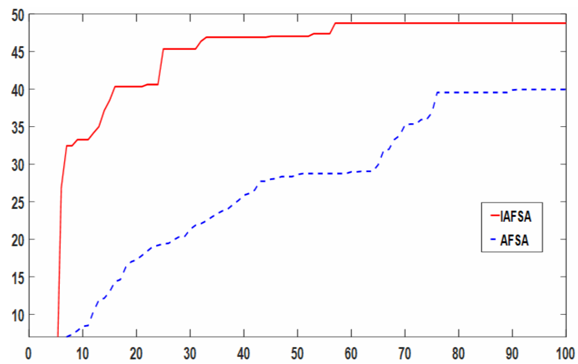

Figure 13. Optimized contrast chart when $\delta = 0.3$

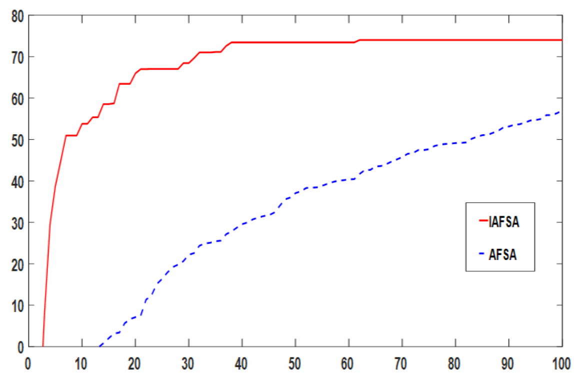

Figure 14. Optimized contrast chart when $\delta = 0.5$

firstly summarizes the research results of the existing portfolio model so that people has a deeper understanding of the portfolio problem. On this basis, a portfolio model with transaction costs is established to make it more in line with the actual securities investment market. Then this paper chooses the stock exchange price data of five stocks in Shanghai stock exchange for 100 days. Finally, the improved algorithm is used to solve the portfolio model, the effect is better, while the investment income increased significantly and the risk has been effectively controlled at the same time. This plays an important role in promoting investors' investment and trading activities, and is conducive to the prosperity and development of the securities trading market.

Although the convergence performance of the improved algorithm has been enhanced, but the effect is still limited, for example, the speed of convergence can be faster, to solve this problem, we can change the four behaviors of the algorithm to global search. It is highly desirable to improve our study further more.

Acknowledgements

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions during the revision of this paper.This work was supported by the "Scientific Research from the Education Commission of Tianjin", No. 2017SK077; "Tianjin Enterprise Technology Commissioner project", No. 19JCTPJC51600.

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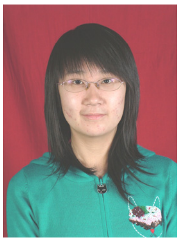

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