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Analysis of performance of green finance and securities investment fund and its social responsibility investment

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Abstract. In order to improve the precision of related analytic model in the application of performance analysis of the Green Finance and Securities Investment Fund and its social responsibility investment, this paper presents an investment performance analytic predictive model based on factor autoscaling particle swarm optimization (PSO). First of all, the problem of the investment performance was analyzed, according to the Markowitz theory and on the basis of consideration of the general investment performance analysis model, combined with market value constraint and upper bound constraint, the investment performance analysis model was modified to obtain a mixed constraint investment performance analysis model; secondly, The particle swarm optimization was introduced into the analysis of investment performance analysis model and its mixed constraint investment performance analysis model was used to solve the problem, in addition, in order to improve the performance of PSO algorithm in the process of model solution, the parameters of PSO algorithm are adaptively learned by using factor automatic-scaling to improve the convergence of the algorithm; finally, the simulation experiments on some stock samples from the board of samples of agriculture, forestry, animal husbandry and fishery showed that, the algorithm presented in this paper can obtain a more ideal investment performance analysis scheme, so as to reduce investment risk and gain more investment incomes.

Key words. Factor auto-scaling, Particle swarm, Investment performance analysis, Quadratic programming.

1. Introduction

Since the 18^{th} National Congress of the Communist Party of China, the direction of financial reform is gradually biased towards the development of the capital market on many levels, the essential developmental direction is the perfection of the financial mechanism, the State Council attaches great importance to the financial risk, and advices and requirements are introduced to strengthen the healthy operation of

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capital market , realizing the decentralized control of financial risk. The so-called decentralized control of financial risk requires the financial institutions and investors, in the process of investment, to fully consider the trade-off between income and risk. Under the environment of ever-developing domestic capital environment, how to operate the capital effectively and reduce the risk of investment is an important research topic in the current situation of social development [1∼2].

In order to calculate the effective boundary of the investment performance analysis model, how to obtain more accurate weights in the process of asset calculation is the key to solving the problem. In this aspect, in addition to some classical algorithms, the evolutionary computation can also be used. James, an American scholar, based on the behavior of bird flock in the course of foraging, has designed an algorithm of evolutionary computation , leading to the establishment of PSO algorithm [3]. PSO algorithm models the foraging bird flock as a "particle", and the algorithm is solved by optimization in the search space that has been set. The particle in the algorithm contains two main attributes: the adaptive value and the flight direction, the former can be determined by the optimization function that has been set, and the latter can be determined according to the direction parameter. In algorithm optimization, the particles of the algorithm all move towards the particle having the best position in the flock.

The computational speed of particle swarm optimization is related to the development level of computer hardware, and the performance of the algorithm has been improved with the development of hardware. In recent years, with the development of investment performance analysis, the evolutionary computation has been used more and more widely. For example, the literature [4] uses the ant colony algorithm for principle analysis and modeling of the stock market investment problem, and uses it to calculate the model weight. The literature [5] takes the income of stock equity as the main research object, and it takes the expected income as the main constraint condition, and focuses on the solution to minimization of weight of expected income to obtain the optimal equity return. The literature [6] uses the genetic algorithm to study the issue of performance analysis of equity investment, and improves the coding process of the algorithm in the process of model solution, and the experimental results show that the proposed method has a better performance in investment performance analysis and optimization.

The literature [7] focuses on the study on the return rate problem of investment performance analysis and compares it with quadratic programming problem, so as to analyze the performance advantage of the proposed algorithm in the issue of investment performance analysis. The literature [8] mainly focuses on the quantity of investment performance analysis on the same income level for the purpose to minimize the quantity of investment performance analysis. The literature [9] uses binary method to encode the combined weight of stock, in order to obtain an optimization function, and taking the risk and the income as two targets that can be balanced, which can form a multi-objective investment performance analysis optimization problem, and finally the differential Evolution algorithm is used to realize the model solution.

The literature [10] replaces the binary coding with integer coding, and improves the genetic algorithm, and then applies the improved algorithm to the solution of the investment performance analysis model. In the literature [11], specific to the restriction of transaction cost , the investment risk preference parameters is used, the optimization algorithm is mainly genetic algorithm, which sets the constraint as the maximum value of the upper limit of investment . In the study of the above algorithms, there are two problems: one is the optimal performance of the algorithm, the problem of ensuring the convergence of algorithm; the other is the scientific evaluation of effect, and the performance of the algorithm lacks of effective evaluation index.

This paper mainly uses PSO to study the investment performance analysis, which mainly involves two aspects, one is the improvement of algorithm performance and the other is the evaluation of the effective rate of algorithm. The major research direction is to compare the theoretical boundary of the precise investment performance analysis with the predicted boundary of investment performance analysis that was obtained in this paper, so as to realize the effective evaluation of the algorithm performance. The precise boundary of investment performance analysis is mainly solved by quadratic programming method. The innovation of this paper is to analyze the PSO of the investment performance analysis, and to group the stocks that were studied, and the distribution interval of each group ranged from 5 to 400. At the same time, three kinds of constraint conditions were used to improve the investment performance analysis model, and the subjects in three groups underwent an experimental and result analysis.

2. Investment performance analysis model

2.1. Efficient boundary of investment performance analysis model

The following steps have to be considered by the investor when making a decision in investment performance analysis: 1) solve the efficient investment performance analysis with the selected stocks and securities to obtain the combined weight accordingly; 2) analyze the expected return rate and investment performance analysis variance to obtain the weight calculated value of investment performance analysis; 3) conduct an analysis through the points on the boundary of investment performance analysis model to obtain the weight calculated value of investment performance analysis. Thereinto, the most crucial thing is to calculate the efficient value of boundary of investment performance analysis in the model (1) as follows, and to obtain the management weight optimization of investment performance analysis:

$$\begin{cases} \min f_1 = x' \sum x \,, \\ \max f_2 = \mu' x \,, \\ s.t.\ x \in S \,. \end{cases} \tag{1}$$

Where, $\sum$ is the covariance matrix of the issue of investment performance analysis, x is the weight vector of each model of the issue of investment performance analysis, S is the study feasible region of the issue of investment performance analysis, μ is the expected return rate. The traditional computational methods used for investment performance analysis include: constraint method, weight summation, quadratic programming optimization computational method and so on. This paper chose the quadratic programming optimization computational method to calculate the precise boundary.

2.2. Quadratic programming optimization computational method

Among The above algorithms, quadratic programming optimization computational method is usually used to realize the optimization of management weight of investment performance analysis, what is obtained by such method is not the precise boundary of the issue of investment performance analysis, but the roughly estimated result of efficient boundary[13].

By study and analysis, Markowitz has designed a key line solving method, which analyzes the investment performance analysis model (1) with the weighting method, the weight parameter is retained in the model, which has changed the way of traditional calculations which take the parameter as beforehand variable, such a method is called quadratic programming method.

Compared with the constraint method and weight summation method and other traditional algorithms, quadratic programming method can realize a precise solution of efficient boundary, instead of rough estimation. Meantime, the greatest advantage of quadratic programming method lies in that, it can reveal the efficient combination of investment performance analysis that is hyperbolically connected at the front and back, and realize the acceleration of computational process.

2.3. Model design

To realize a performance analysis in the course of PSO for investment performance analysis model, this paper has studied two crucial indexes, investment performance analysis constraint and investment performance analysis number. The number of stock grouping n is $n = [5, 10, 50, 100, 200, 300, 400]$. Then, using different constraints to set, the PSO method and quadratic programming method proposed in this paper were used to solve the efficient boundary of the issue of investment performance analysis, by which the effective rate evaluation index was obtained , the specific procedure is shown in the block diagram in Fig.1

Group 1: select the standard model for the issue of investment performance analysis, which is as follows:

$$\begin{cases} \min f_1 = x' \sum x\,, \\ \max f_2 = \mu' x\,, \\ s.t.\ 1'x = 1; x \geq 0\,. \end{cases} \tag{2}$$

Group 2: apply a upper limit constraint to the choice problem of standard investment performance analysis in the formula (2), a combined modified model shown in the formula (4) can be obtained, where, u is the upper limit of standard investment performance analysis model, 1 is the vector whose element is 1, 0 is the vector whose element is 0:

$$\begin{cases} \min f_1 = x' \sum x\,, \\ \max f_2 = \mu' x\,, \\ s.t.\ 1'x = 1; 0 \leq x \geq u\,. \end{cases} \tag{3}$$

In this study, the stocks whose number is 5 and 10 were studied, and the upper limit of these two groups was set as 0.4, the upper limit of the stocks in the other groups [100, 200, 300, 400] was set as 0.1.

Group 3: use the market value constraint to modify the standard investment performance analysis model shown in the formula (1), see the formula (5), where, parameter m is the market value of stock among the objects of study that have been chosen, it is a numerical vector.

$$\begin{cases} \min f_1 = x' \sum x\,, \\ \max f_2 = \mu' x\,, \\ s.t.\ 1'x = 1; m'x \geq m\,. \end{cases} \tag{4}$$

In this study, the market value vector of object of study, m, is the mean value of market price of the stock that is denoted by it.

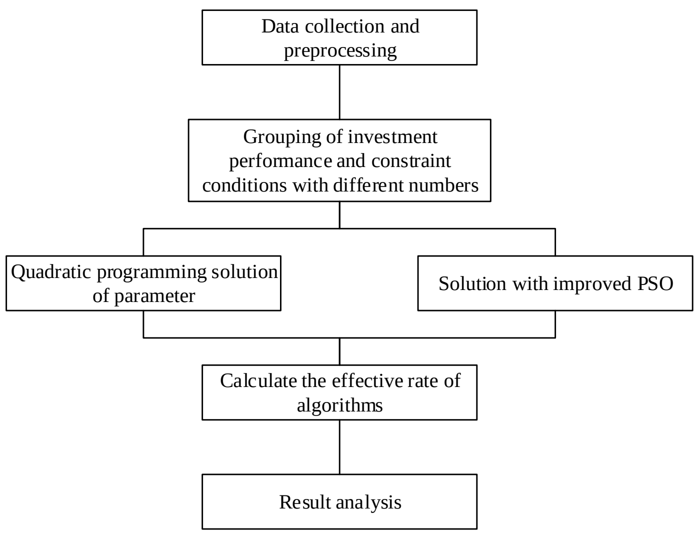

Fig. 1. Algorithm efficiency evaluation process

3. Modified PSO based on factor auto-scaling

3.1. Basic PSO algorithm

In the computation of PSO algorithm, the particle swarm is randomly initialized as the random candidate solution for the group 1, the optimal solution is obtained through the evolution process. In the process of PSO solution, each particle realizes the renewal of foraging position through tracking the two extreme value particles. One of These two extreme value particles is the optimal solution of PSO swarm, p_{best}; the other one is the historically optimal value g_{best} of the particle itself; PSO's specific model is shown as follows:

The evolutionary real-time position of particle i in PSO is set as $X_i = (X_{i1}, X_{i2}, \ldots, X_{in})$; the real-time speed of particle i in PSO is $V_i = (V_{i1}, V_{i2}, \ldots, V_{in})$; the optimal position of particle i in PSO during historical evolution $P_i(t) = (P_{i1}, P_{i2}, \ldots, P_{in})$, that is, the best position the particle i has experienced in PSO is the best position for the individual particle.

As to the minimized solution for model, it means the smaller the target, the better the position represented by the particle. It can be worked out that, the best particle position in current algorithm of PSO $P_g(t) = (P_{g1}, P_{g2}, \ldots, P_{gn})$, which is also known as the best adaptive value (position) of PSO population. Then the standard particle swarm evolutionary model is:

$$\begin{aligned} &V_{ij}(t+1) = V_{ij}(t) + c_1 r_{1j}(t) \\ &(P_{ij}(t) - X_{ij}(t) + c_2 r_{2j}(t)(P_{gj}(t) - X_{ij}(t)) . \end{aligned} \tag{5}$$

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{6}$$

Where, the subscript "j" of the parameter denotes the particle whose dimension is j in the swarm, in a similar way, the subscript t denotes the number of generations of particle swarm evolution, "i" is the particle i in the swarm; c_1 and c_2 is the acceleration constant of PSO, the value-taking interval is 0$\sim$2. the random function $r_1 \sim \bigcup(0,1)$ and $r_1 \sim \bigcup(0,1)$ are mutually independent.

According to the particle evolution model shown by the formula (5)$\sim$(6), there are two parameters in the model, c_1 and c_2, the role of former is to adjust the evolutionary direction of particle, and make it evolve towards the direction of best position for it all along; the role of latter is also to adjust the evolutionary direction of particle in the algorithm and make it evolve towards the direction of globally best position. To prevent the PSO particle from flying away from the value-taking interval during the evolution, the value-taking interval of V_{ij} will usually be set, namely, $V_{ij} \in [-V_{\max}, V_{\max}]$. If the value-taking interval of investment performance analysis issue is $[-V_{\max}, V_{\max}]$, then $V_{\max} = k \cdot X_{\max}$, where $0,1 \leq k \leq 1.0$, based on which, the PSO can be initialized with the following steps:

Step 1: the population size parameter of particle swarm optimization is set as N;

Step 2: in the interval $[-X_{\max}, X_{\max}]$, the uniform distribution function is used to choose the population individual x_{ij} for the particle in the population whose subscript is i and j

Step 3: in the interval $[-X_{\max}, X_{\max}]$, the uniform distribution function is used to choose the population individual y_{ij} for the particle in the population whose subscript is i and j

Step 4: a relation is set as $y_i = x_i$ for the particle whose subscript is i in the population.

The computational flow of the standard PSO algorithm is:

Step 1: According to the initialization steps of the PSO algorithm, the velocity and position information of the particle swarm algorithm is initialized;

Step 2: Calculate the adaptive value of all the particles in the particle swarm algorithm;

Step 3: The historically optimal position P_i of all the particles in the PSO algorithm is compared with their current adaptive value, and if the current position adaptation value is better, then it is regarded as the best position for the current particle.

Step 4: For all the particles in the PSO algorithm, the globally optimal position of all the particles is compared with its current adaptive value, and it is regarded as the best position for the current particle if the current position adaptation value is better;

Step 5: According to the evolution model of the standard PSO algorithm, the position and velocity model of particle swarm optimization are updated;

Step 6: If the PSO evolution process does not meet the preset termination condition, then skip to Step 2 to continue the algorithm evolution.

3.2. Factor auto-scaling modification

The main problem of PSO in convergence is the premature convergence, in order to effectively avoid such a problem, the factor auto-scaling process is introduced into the PSO, through the diffusion and attraction of factors, the particle swarm individual is allowed to presente with more diverse characteristics with a better convergence rate. The modified velocity evolution model of the proposed factor auto-scaling PSO is as follows:

$$\begin{aligned} V_i(t+1) =& \chi(V_i(t) + dir(c_1 r_1(P_i - X_i(t)) \\ &+ c_2 r_2(P_g - X_i(t)))) \end{aligned} \tag{7}$$

Where :

$$dir = \begin{cases} -1, & if(dir > 0)\&(diversity < d_{low}) \\ 1, & if(dir < 0)\&(diversity > d_{high}) \end{cases} \tag{8}$$

Meantime, the form of model of population to maintain the diversity is presented as:

$$diversity(S) = \frac{1}{|S| \cdot |L|} \cdot \sum_{i=1}^{|S|} \sqrt{\sum_{j=1}^{N} (P_{ij} - \overline{P_j})^2} \tag{9}$$

Where, S is the swarm used by the PSO for evolution, $|S|$ is the number of individuals in this evolution swarm, $|L|$ is the maximal interval radius of the search interval of particle swarm, N is number of dimensions during the particle swarm evolution, P_{ij} is the component j of particle i. In the evolution of PSO, if the individual diversity of swarm meets the condition $diversity(S) < d_{low}$, then dir can be set as -1, at that time, the particle swarm evolution is terminated, and move towards gradually the direction far away from this position, this process is called "diffusion".

Meantime, if the diversity of individual of particle swarm increases, and exceeds its upper limit, then dir can be set as 1, at that time, the particle swarm evolution moves towards the direction of best position, this process is called "attraction". At the same time, d_{low} is set as 5.0×10^{-6}, d_{high} parameter as 0.25; then,

$$\chi = \frac{2}{|2 - \ell - \sqrt{\ell^2 - 4\ell}|} \tag{10}$$

Where, parameter $\ell = c_1 + c_2$, $\ell > 4$, parameter $c_1 = c_2 = 2.05$, and $\ell = c_1 + c_2 = 4.1$ is substituted into the formula (10), a model result $\chi = 0.7298$ can be obtained, then substitute this result into the formula (7), then:

$$\begin{aligned} &V_i(t+1) = 0.7298(V_i(t) + \\ &dir(2.05r_1(P_i - X_i(t) + 2.05r_2(P_g - X_i(t)))) \end{aligned} \tag{11}$$

As $2.05 \times 0.7298 = 1.4962$, then it can be known that, this model is equivalent to the one obtained with the parameter $c_1 = c_2 = 1.4962$ and $W = 0.7298$ that are used in the speed renewal model in the course of standard PSO evolution.

4. Simulation experiment

4.1. Simulation environment

In order to verify the effectiveness of the improved particle swarm optimization (PSO) in analyzing the Investment performance process, the hardware platform: CPU i5-6500K and RAM 6G ddr4-2400k have been chosen , the simulation system was run on a platform installed with Win7 flagship version. The genetic algorithm and standard particle swarm optimization algorithm have been chosen as a control algorithm. The following two datasets were chosen as The experimental dataset:

Simulation Data 1: some stocks from the board of agriculture, forestry, animal husbandry and fishery were chosen as experimental object, the time interval was from January 2012 to December 2016 with a total of 50 months of stock yield, the stock market value on November 20, 2016 was selected as the stock market value result. The selected stock data was used to select the Stock samples, the sample integrity parameter is set as 95%, and 460 groups of stock sample can be screened out according to the condition. Then from the Stock samples, seven groups of experimental data sample with different quantities were selected, which were 6, 12, 54, 108, 215, 330 and 400, of which the stock groups whose quantity was

6, 12 and 54 contained 6 subgroups respectively, the stock group whose quantity was 108 contained 5 subgroups, the stock group whose quantity was 215 contained 3 subgroups, and the stock group whose quantity was 330 and 400 contained 2 subgroups respectively.

Simulation data 2: among some stock groups in the board of agriculture, forestry, animal husbandry and fishery that had been chosen, 10 most representative stocks were chosen, the information about the chosen stocks is shown in the table 1.

Table 1. Stock data

No.	Stock code	Stock brand name	Earning per share (yuan)
1	002041	Shandong Denghai Seeds	24.6
2	600598	Beidahuang	25.2
3	002447	Yiqiao Share	16.8
4	000735	Luo Niushan	24.2
5	002321	Huaying Agriculture	22.02
6	600108	Yasheng Group	15.1
7	000998	Longping High-Tech	22.4
8	000592	Pingtan Development	16.0
9	600257	Dahu Shares	21.8
10	600965	Fucheng Shares	18.0

4.2. Simulation data 2 experimental result

According to the results shown in Figure 2, as for a preset constraint (2∼4), if the number of selected stock samples increases from 6, 12, 54 to 410, among the selected comparison algorithm, the effectiveness of genetic algorithm in analyzing investment performance of stock samples showed a downward trend, that is, the index is inversely related to the number of stock samples . If the stock sample number is 6, the efficiency index of the comparison algorithm GA on the issue of three groups of investment performance analysis is 95.12%, 98.42% and 81.35% respectively. If the number of stock samples increases to 410, the efficiency index of the comparison algorithm GA on the issue of three groups of investment performance analysis decreased to 60.48%, 58.21% and 53.68% respectively,

In addition, seen from the experimental results, of all the selected comparison algorithms, the genetic algorithm always has the lowest efficiency index on the selected number of different samples .

4.3. Simulation data 1 experimental result

Similarly, the GA and PSO algorithm were selected for a comparison, what is shown in the Fig.3 is the process of evolution of adaptation of GA and PSO with the evolution course.

As shown in Fig. 3, compared with the two comparison algorithms, GA and PSO, the algorithm of this paper has a better convergence speed obviously, and at the same time, the convergence volatility of global extremum of the algorithm of this paper is not significant in the later stage of algorithm evolution. The results

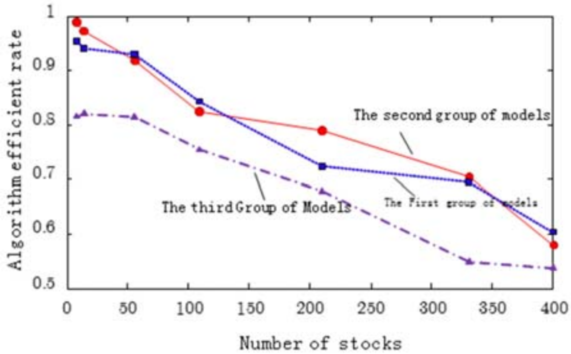

Fig. 2. Comparison of efficiency indicators

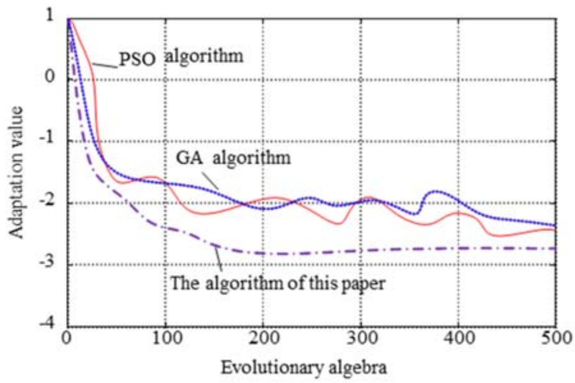

Fig. 3. Adaptation comparative curve

shown in the Fig. 3 show that, the algorithm of this paper has a relatively superior stable solution and it is more accurate. Compared with GA and PSO algorithm, the algorithm of this paper is less likely to fall into local extremum. The optimal calculation results of the three selected methods are shown in table 2.

Table 2. Optimal solutions of the algorithms

Algorithm	GA	PSO	IAFS
1	0.165	0.155	0.161
2	0.123	0.144	0.140
3	0.052	0.142	0.131
4	0.065	0.039	0.049
5	0.121	0.143	0.098
6	0.194	0.027	0.062
7	0.007	0.117	0.122
8	0.065	0.031	0.046
9	0.140	0.011	0.017
10	0.060	0.184	0.169
Optimal solution	-0.241	-0.273	-0.293

According to the results shown in table 2, for the same preset constraint, the algorithm of this paper has a smaller investment risk, and its investment scheme is more reasonable, the investor has a higher satisfaction. The above experimental results show that, the proposed algorithm in this paper is highly efficient in solving the investment performance analysis model and has a more excellent performance.

5. Conclusion

This paper presents an investment performance analytic predictive model based on factor autoscaling particle swarm optimization (PSO).

According to the Markowitz theory, the investment performance analysis model is improved, and a mixed constraint investment performance analysis model is obtained, and the particle swarm optimization is introduced to optimize and analyze the investment performance analysis model. The experimental results show that, the algorithm of this paper has a better performance compared with the two comparison algorithms , GA and standard PSO, and it can achieve a more ideal investment performance analysis scheme, so as to reduce investment risk and gain more investment income.

In the background of China's economic development, financial market has also been developing rapidly, in the process of investment, the risk of investment in financial market needs to be diffused , so that investors can grasp the investment information in a more accurate way, reducing the risk of investment. Although the real stock samples are chosen and analyzed by the algorithm of this paper, the analysis results in a real environment still needs a further analysis and verification.

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