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Research Article

Research on Prediction of Investment Fund's Performance before and after Investment Based on Improved Neural Network Algorithm

Cong Gu

College of Science, Zhongyuan University of Technology, Zhengzhou, 450007 Henan, China

Correspondence should be addressed to Cong Gu; gucong@zut.edu.cn

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There are more and more popular investment fund projects in the continuous economic development; the prediction and performance continuity become hot topics in the financial field. Scholars' enthusiasm for this also reflects the domestic fund primary stage progress, and there is a huge application demand in China. The prediction of fund performance can help investors to avoid risks and improve returns and help managers to learn more unknown information from the prediction for the sake of guide market well and manage the market orderly. In the past research, the traditional way is to use the advantages of neural network to build a model to predict the continuous trend foundation performance, but the author found that the traditional single neural network (NN) algorithm has a large error value in the research. With the discussion, the particle swarm optimization (PSO) algorithm is added to the radial basis function (BRF) neural network, and PSO is conditioned to optimize and improve the RBF NN combining the advantages of both sides; a new set of PSO-RBF neural network security fund performance prediction method is summed up, which optimizes the structure and workflow of the algorithm. In the research, the author takes the real data as the reference and compares the prediction results with the traditional method RBF and the improved PSO-RBF. In the prediction results of the continuous trend, the highest value, and the lowest value in the period of the security fund performance, the new PSO-RBF has a good prediction in the fund performance prediction, and its accuracy rate is greatly improved compared with the traditional method Sheng, with good application value, and is worth popularizing.

1. Introduction

Since the establishment of investment fund, the fund industry has developed rapidly. The scale is getting bigger and bigger and more and more varieties; it has greatly improved the structure of investors and played an increasingly stable and healthy evolution historical securities. Although domestic fund has made considerable progress in the past eight years, compared with the mature western market, the scale is still small. At present, there are more than 8000 kinds of funds in the US financial market, far higher than the number of listed company, while there are 642 in China. Investment funds have great potential in China [1].

The sustainability of fund performance refers to the phenomenon that a better fund will perform relatively well earlier in the future, while a worse fund will perform relatively poorly in the future, which is often called "strong often strong, weak often weak." By concept, suppose the investor can identify early excellent performance of the fund and continuous performance, can be purchased these capital and holdings them after a period, so as to obtain the above average excess return. Similarly, poor performance can be avoided if investors are able to identify funds with poor early and sustained performance and avoid investing in them. From this point of view, performance sustainability characteristics are undoubtedly as important as fund performance itself.

Final performance of security forecast is very central link to promote sustainable development of security fund. In a mature market, it means a lot for buyer, manage company, and function supervision to predict fund performance scientifically and objectively. Helping the buyer, through the

analysis of security market, we can get the accurate information of fund investment effect, adjust the investment strategy in time, and make the right investment choice. For fund management companies, scientific evaluation of their fund performance can not only give a quantitative evaluation of specific performance to each fund manager but also determine the advantages and disadvantages of investment strategies, summarize successful experience, improve the deficiencies, and improve the management level of the company. For regulators, they can formulate various relevant policies and regulations based on scientific security performance and management effect. Since the 1990s, the in-depth research on the prediction, optimization, and control of the financial system, as well as the extensive application of information and control theory and technology in the current financial problems, have brought challenges to the development of financial engineering. Financial forecast is an important part of financial engineering. For financial investors, it is difficult to explain the inherent laws of stock price, return, and risk of financial derivatives by using the traditional time series prediction technology. In recent ten years, neural network theory has gradually become a powerful tool for nonlinear dynamic system prediction and modeling. From the origin to now, the research and application of artificial neural network have entered a mature stage, and the application field is also expanding. At present, NN is mainly used for price prediction, trend, and rise of the stock market, with relatively high prediction accuracy [2, 3].

By simulating the structure of human neurons, neural network has a strong ability of self-learning, self-organization, and memory. It can predict the future development trend of stock price according to the historical data and relevant information of stock market. RBF NN is an infinite approximation and outstanding goodness of fit. Hence, RBF NN can be used as stock price prediction with high complexity. In this article, the basic principle of RBF NN is described in detail, and the gradient descent for RBF NN algorithm is analyzed. In the initial stage of global search, PSO is proved to be fast and effective. Based on the advantages and disadvantages of the two algorithms, this mentioned in the article hybrid computing method combines PSO calculation method and RBF algorithm exercise of front NN weight, which is called PSO-RBF computing method. Mixed calculation method not only uses the powerful global search power PSO algorithm but also uses the powerful search ability in the range of RBF calculation method. Case study of security performance of PSO-RBF NN, in this paper, discusses the basic concepts and structural characteristics of RBF and PSO. For different optimization algorithms, an optimization algorithm based on RBF neural network and particle swarm optimization algorithm is proposed. The working process and principle are introduced in detail, and the actual data are compared. In the comparative study, we find that the new calculation method is better than the traditional one security fund performance prediction, and its accuracy has been greatly improved. Experimental best results show that improved algorithm for PSO-RBF NN has rich value in fund performance research, and the model has a good application prospect [4–6].

2. The Development and Research of Security Fund Performance Prediction

2.1. The Concept and Characteristics of Security Investment Fund. Fund refers to a method of collective investment sharing benefits and risks. The funds of investors are centralized through the funds of public issuance of shares, which are entrusted by the fund custodian, management use, and control, and invested the remaining, other helpful market tools of the fund holders.

Different countries have different names for fund, considered as "shared fund" in the United States; Britain and Hong Kong are called "unit trust fund"; Japan and Taiwan are called "Investment fund."

Fund can rapidly develop into popular investment tools, which is closely related to its own characteristics:

(1) Security investment funds are widely invested in different securities, which can fully disperse risks

Due to the limited funds, small- and medium-sized investors generally cannot reduce the risk through fully diversified investment. And fund not only has the abundant capital strength but also can fully disperse the investment in various securities and realize the diversification of the asset portfolio. This diversification reduces the risk faced by each investor. Even if some securities have poor performance or even loss, they can be made up by other securities with excellent performance to achieve the purpose of dispersing investment risk.

(2) Security investment funds are managed by experts, professional financial management, and collective investment

The fund collects the funds of many investors, which are handed over to professional institutions and invested in various financial instruments by professionals with solid professional knowledge and rich investment experience. At the same time, investors can also decide the amount of investment according to their own economic situation. Although each investor does not invest much capital, because the fund can collect a lot of investors' funds, it rarely enters, controls costs, and gives play to the advantage of capital scale.

(3) Security investment funds have good supervision system and reasonable operation mode

The regulatory authorities strictly regulate fund industry and require the fund to disclose sufficient, timely standard message. In operation, foundation custodian keeps foundation assets independently, which is conducive to the safety of the fund assets. The principal supervises the purchase and operation activities of the investment manager and conduct accounting and performance calculation for the fund assets, which is conducive to protecting the interests of shareholders [7, 8].

2.2. The Development Course and Current Situation of Security Investment Fund in China. The fund established before 1997 is called "old fund," which mainly invests in

industry, but actually is a direct investment fund. In the real sense, security investment fund has experienced the development stages of closed-end fund and open-end fund since 1998.

The second stage (from September 2001 to now): the fund has entered an open development stage.

After 2001, China's fund scale expanded rapidly, the innovative varieties began to accelerate, and the supervision of the fund industry continued to strengthen. By the end of 2007, 59 fund management companies had been established in China, 9 of which had assets under management of more than 100 billion yuan. The number of funds reached 345, including 310 unrestricted form funds and 35 restricted form funds. Open-end funds account for 90% of the total funds. The total value of the fund is 3.28 trillion yuan. The asset performance of the unrestricted fund is 3.04 RMB 100 million, accounting for 92% total fund performance. Unrestricted fund has become the mainstream of market evolution instead of closed-end fund.

Despite China's portfolio investment fund industry has developed rapidly current stage, it is an emerging market after all. Compared with the development of the history of financial power more than 100 years, there is still a significant gap. In order to ensure the further sustainable development of financial market, many problems need to be solved to coordinate the expansion of fund scale and asset management level: to prevent the moral hazard number of fund managers; to further improve the internal governance structure of fund management companies; to implement incentive mechanism to weaken the frequent change of fund managers; to increase financial innovation and change the fund portfolio to be the same [9, 10].

2.3. Research on Fund Performance Forecast and Its Influencing Factors. At present, there are few studies speaking of performance prediction of direct domestic fund. Only the prediction method based on Markov chain proposed by Liu Tie thinks that according to the previous data of the fund, the probability of fund performance falling in each interval and the probability of fund performance falling in each interval can be predicted. However, when the fund managers' strength of stock selection is constantly studied, the impact of fund and fund managers on fund performance changes, such as some niche studies: to study the strength of fund managers to choose stocks, although the basic T-M and H-M models are adopted, but because the selected research scope is different, there are great differences in the conclusions. In recent years, continuous fund performance discussion is very popular, but the results are different. Tang Zhenyu made data analysis on the merger of small- and medium-sized enterprises in China, June 1008, 2003, and think the performance of domestic fund managers is sustainable. By analyzing the performance and risk sustainability of equity funds and from 2004 to 2008, the mixed fund in domestic unrestricted fund are in different performance markets; Yang found that only in 2004-2005, the risk-adjusted fund performance can be sustained. When the market enters the period of shock adjustment from bull market, the fund performance appears reversal phenomenon, and the risk has obvious continuity. With regard to the change of fund managers, studies by domestic scholars such as Xiong Shengjun, Yang Chaojun, and Xu Xiaolei show that the change of fund managers in China has no impact on fund performance [11, 12].

2.4. Application of Neural Network in Fund Performance Prediction. The development of artificial intelligence provides a new method for fund performance prediction. Among them, NN has a strong nonlinear property data processing ability, which is very suitable for fund performance prediction. BP NN is used to establish the fund performance and guess the model. The data shows that the prediction accuracy of BP NN is high and is better than that of traditional linear prediction model. But BP NN is easy to fall into local optimum minimization and slow convergence, so BP neural network is not the best fund prediction method. Compared with BP NN, RBF NN is a better choice to predict the performance changes of nonlinear funds. However, RBF neural network itself has some disadvantages, such as slow convergence speed and no global search ability [13, 14]. Therefore, RBF neural network is not the best method to predict fund performance. Sample data, the author of this paper, a reasonably constructed index system for fund performance change, is trained and tested by using the nonlinear processing ability and PSO RBF NN has better overall search capability and sample data set. The BP NN and RBF NN are fully avoided from slow speed and easy access to local minimum dilemma in the process of predicting fund performance, and the accuracy of fund sale performance prediction is greatly improved [15–17].

3. Research and Methods

3.1. Particle Swarm Optimization Algorithm. PSO is a kind of evolutionary computing technology, which originated from the study of bird feeding. Now, it has been proved to be a good optimization method. PSO calculation method can be similar to an abstract scene. There is a piece of food in an area, and many birds look for that piece of food randomly in different areas. Where is the food? Birds do not know; they only know the approximate distance of the food and how the information is transmitted from one population to another, so the problem of finding food has become that each bird looks for food nearby. PSO has inspiration through the model and uses optimization solved problems. The result of every optimization problem in PSO can be understood as a bird in search space, which is called "particle." Particles can fly in search space according to a certain trajectory and speed, which is dynamically adjusted by their own speed and flight information. Birds imagine a point without mass and volume and develop it into n-dimensional space. The position of the i th particle in space can be displayed by vector $x = (x_{i1}, x_{i2}, \cdots, x_{\mathrm{iN}})$. The speed of flight can be displayed by vector $v_i = (v_{i1}, v_{i2}, \cdots, v_{\mathrm{iN}})$. The best place in history is called personal extremum. So far, all particles are in the most suitable position; whole population is called global extreme value gbest. In particle swarm optimization, all particles have corresponding fitting the value is optimization function, and the

individual extremum pbest and global extremum gbest are determined by the minimum fitting value of each particle [18–20].

3.2. Application Research Status. For the first time, the PSO calculation method is applied to the optimization of nonlinear continuous functions and the training of neural networks. Eberhart uses particle swarm optimization to analyze tremors, such as Parkinson's disease. Yoshida et al. optimized various discrete continuous variables through PSO to control the output stable voltage of nuclear power unit. Robinson et al. use PSO calculation method optimization of profile wave horn antenna, compared the optimization effect with genetic algorithm, and studied the feasibility of their hybrid application. Ciuprina proposes intelligent PSO (intelligent PSO) to optimize the size of the solenoid coil. Abido uses PSO calculation method to solve the most typical problems. In China, more and more scholars also pay attention to the application of the algorithm, which shows a good application prospect of multiobjective optimization, data classification, data gathering, pattern identification, telecom service quality management, process planning, signal processing, intelligent machine control, decision reference, and true and false identification system identification [21–23].

3.3. RBF Neural Network

(1) Introduction to the structure of RBF NN

RBF NN consists of three parts. The nonlinear mapping is completed as shown below.

$$f_n(Y) = s_0 + \sum_{q=1}^{n} s_q \varphi(\|y\text{-}u_q\|), \tag{1}$$

where $Y \in K_n$ is the write in vector and $\varphi(\bullet)$ is a nonlinear ability of $K^+ \to K$. Generally, Gaussian function is adopted:

$$\varphi(\|Y\text{-}U_q\|) = eyp\left(-\frac{\|y\text{-}u_q\|^2}{\sigma_q^2}\right). \tag{2}$$

w_i is the weight, c_i and σ_i are the data sets and base ability, and h is the coding of centers.

RBF neural network needs to determine two kinds of parameters: unique center c_i and width σ_i basic function and intermediate value h, one remaining connection weight between write in time and bury time. Here, c_i and width σ_i basic functions and number of centers h are determined; the internet weight value output is linear when it is written in, but obtained by the least square method. Therefore, the determination of c_i, width σ_i, and number of centers h is the construction of the core of RBF NN [24–26].

(2) The determination of the number of centers of basic functions

The kernel subtraction clustering method is kind the optimal calculation method of confirming the number of basic function centers. In this paper, we consider normalizing the data into P numerical value $(Y_1, Y_2, \cdots, Y_p)$ in the n-dimensional space of the unit hypercube. First, we give the degree value of numerical concentration point Y_q by formula (1) [27, 28]:

$$D = \sum_{q=1}^{p} \text{eyp}\left[-\frac{\|y_q\text{-}y_j\|^2}{(\gamma_a/2)^2}\right]. \tag{3}$$

After calculating the degree of aggregation each data point, the point with the highest degree of aggregation selected becomes a hub, and its density index is recorded as D_{c1}. Update the aggregation degree formula of each numerical point (2):

$$D_q = D_q\text{-}\sum_{q=1}^{p} \text{eyp}\left[-\frac{\|y_q\text{-}y_{um}\|^2}{(\gamma_b/2)^2}\right]. \tag{4}$$

After updating each aggregation level, select another cluster center and modify the aggregation level again. Repeat this to solve the maximum density index $D_{\max}$ of the current very small relative to the initial maximum density index, that is,

$$\frac{D_{\max}}{D_{c1}} < \lambda. \tag{5}$$

The number of aggregation cores is the number of basic function cores.

3.4. PSO Algorithm Principle. PSO calculation method was proposed by Eberhart and Kennedy in 1995. It is an evolutionary computing technology that simulates the flight and foraging behavior of birds and seeks the optimal solution through cooperation among individuals. Suppose the search space is n dimension. The number of particles is y, and the orientation of the ith particle in y-dimensional space is $y = (y_{q1}, y_{q2}, \cdots, y_{qh})$, and the speed is indicated as $v_q = (v_{q1}, v_{q2}, \cdots, v_{qh})$. All particles contain an adaptive value determined using update function to master the best position pbest and current position y_q it finds at present. Each particle masters the best position the entire population found successfully. Post of each particle is changed according to formulas (3) and (4) [29–31].

$$\begin{aligned} v_{qd}^{k+1} = w \times v_{qd}^{k} + \eta_1 \times \text{rand}\,() \times \left(p_{qd}\text{-}y_{qd}^{k}\right) \\ + \eta_2 \times \text{rand}\,() \times \left(p_{gd}\text{-}y_{qd}^{k}\right), \end{aligned} \tag{6}$$

$$y_{qd}^{k+1} = y_{qd}^{k} + v_{yd}^{k+1}, \tag{7}$$

where v_{qd}^{k} are d-dimensional flight components speed in the kth iteration ith particle; y_{qd}^{k} is the d-dimensional composite member ith in the particle orientation in the kth iteration; p_{gd} best position is the component of D group; p_{id} is the dth

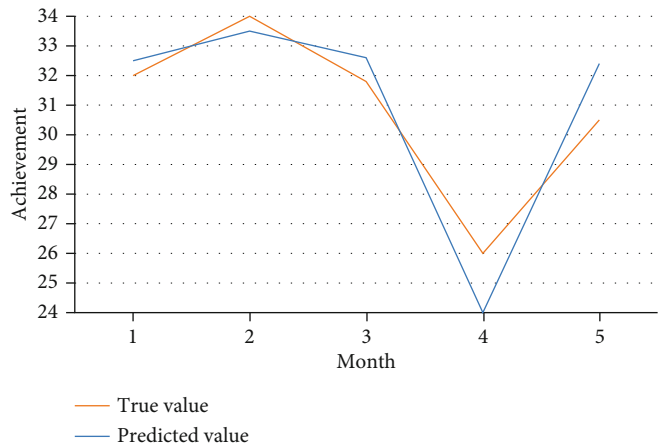

Figure 1: Comparative analysis of RBF neural network algorithm and fund actual performance.

Table 1: Relative error value of average value of RBF neural network for fund performance prediction.

Frequency	1	2	3	4	5	Mean value
Average relative error of test	0.0921	0.0921	0.1069	0.0753	0.0780	0.0953

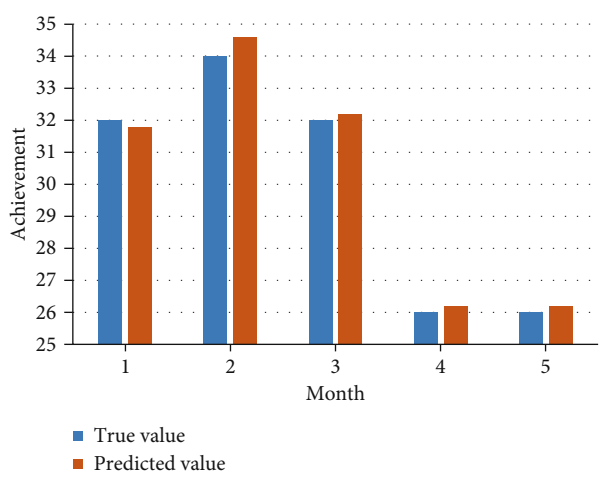

Figure 2: Comparison analysis of PSO-RBF neural network prediction and real fund performance results.

dimension best position member particle I; rand () is the random number of randomly generated [0,1]; η_1, η_2 is the specific gravity factor; S for weight. The solution of S is (5):

$$s = s_{\max} - \frac{s_{\max} - s_{\min}}{Num_{\max}} \times Num, \tag{8}$$

where $s_{\max}$ and $s_{\min}$ are larger and smaller values of s; $Num_{\max}$ and Num are the maximum and current iterations, respectively.

3.5. Learning Algorithm of RBF Neural Network Based on PSO

(1) Encoding and function of PSO calculation method

In particle swarm optimization, particles correspond to dissolvable, so the particle value includes the core value and width of the basic function, particle speed, and sensitivity. If there are m centers, each m is K, then the particle's position is $m \times (T+1)$ dimension, and the corresponding particle velocity should also be $m \times (T+1)$ dimension. In addition, there is another fitness [32, 33]. The coding structure of particles is as follows:

$J_{11} J_{12} \cdots J_{1T} \sigma_1 \cdots J_{21} J_{22} \cdots$
$f(y)$
$V_1 V_2 \cdots V_m \times (T+1)$
$J_{1T} \sigma_1 \cdots J_{m1} J_{m2} \cdots J_{mT} \sigma_m$

The goal of NN exercise is to find the parameters that make the mean square error the minimum, so the reciprocal of the error chosen becomes a fitness ability. Comfort ith individual is:

$$f_i = \frac{1}{R_i}, \tag{9}$$

$$R_i = \frac{1}{N} \sum_{k=1}^{N} (y_k - y\wedge_k)^2. \tag{10}$$

(2) Calculation method steps

Step 1. Collect exercise members.

Step 2. The kernel number of the basic function is determined by clustering the members with kernel subtraction.

Step 3. Initialize the number of particles swarm.

Table 2: Relative error value of average value of PSO-RBF neural network for fund performance prediction.

Frequency	1	2	3	4	5	Mean value
Average relative error of test	0.0162	0.0246	0.0248	0.0231	0.0176	0.0215

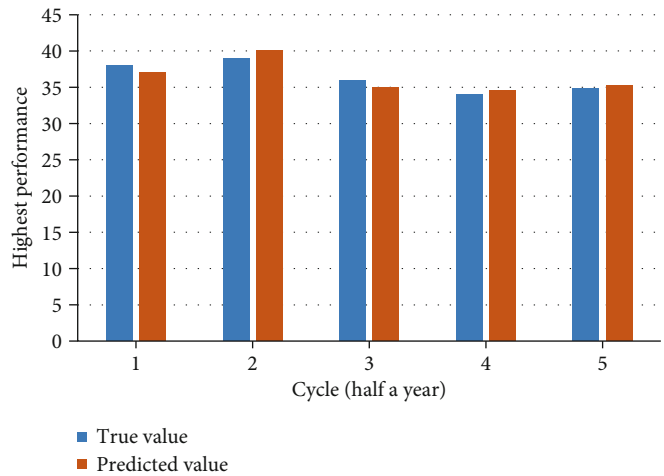

Figure 3: Comparison analysis of the real results of PSO-RBF neural network prediction and the highest fund performance.

Table 3: Relative error value of the average value predicted by PSO-RBF neural network for the highest value of fund performance.

Frequency	1	2	3	4	5	Mean value
Average relative error of test	0.0158	0.0176	0.0169	0.0183	0.0265	0.0196

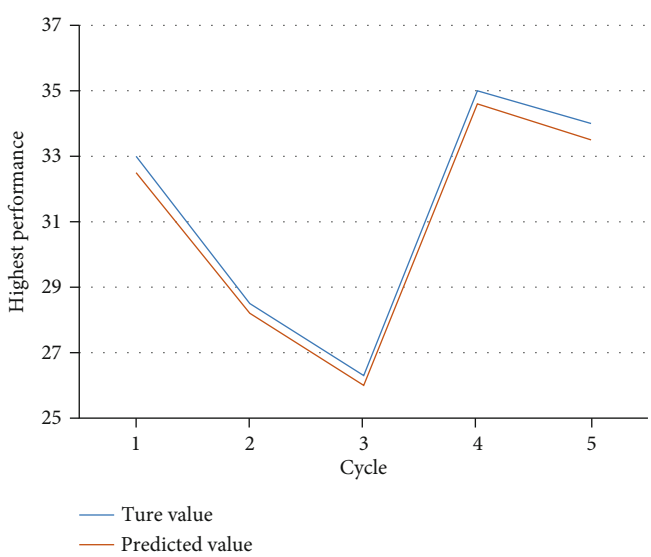

Figure 4: Comparison analysis of real results of PSO-RBF neural network prediction and minimum fund performance.

Step 4. For each particle, compare its fitness with that of the best position it experiences, and update p_{id} if it is better.

Step 5. Compare the comfort of each particle of the best position experienced by the population; if better, update p_{gd}.

Step 6. Adjust the speed and position of particles.

Step 7. Repeat steps 4 to 6 until the calculation requirements are met.

Step 8. Take the decoding value of the best position experienced by the packet as the structural the value of RBF NN, and then, learn.

Step 9. Stop the operation.

4. Experiment and Analysis

In order to further verify that the neural network based on PSO has a good ability fund income estimate, this experiment selects performance of a fund for 5 months as a case study. In this paper, RBF and PSO-RBF are used to predict the performance of a fund in five months, and PSO-RBF algorithm is used to predict the trend of the highest and lowest performance of the fund, so as to study the reliability and accuracy of this research method.

4.1. RBF Algorithm Prediction. The input value is a single vector, which is taking the closing performance of a fund as the input variable exercise radial basis function-based NN and then using the trained network to predict the next time's fund performance. The results are shown in Figure 1.

Table 4: Relative error value of average value predicted by PSO-RBF neural network for the lowest value of fund performance.

Frequency	1	2	3	4	5	Mean value
Average relative error of test	0.0169	0.0175	0.0163	0.0229	0.0187	0.0191

Through the analysis of Table 1, it can be concluded that the RBF neural network algorithm is feasible in theory, but there are some errors in the example analysis. The experiment according to evaluation error is 9.53% five times, and the highest and lowest values are 10.69% and 7.8%. The error is relatively large, which obviously does not meet the requirements in practical application and does not reach the accuracy required in this paper. Because there are such problems in the prediction only by RBF neural network, we need to improve and optimize the algorithm on this basis.

4.2. Prediction of Improved POS-RBF Algorithm. Figure 2 shows the optimization calculation method in PSO-RBF NN. According to the prediction data, we get the consistency between the prediction results and the real data storage trend. In addition, we can see from the relative error table of the average value of the performance forecast in Table 2 that in the five experiments, the error values of 1.62%, 2.46%, 2.48%, 2.31%, and 1.76% are, respectively, obtained, and the error average value is 2.15%. This result is very accurate compared with most of the current prediction methods, and it is a big research difficulty to reduce the error value within 3 percentage points. Especially for the above-mentioned RBF neural network single algorithm want to compare has made obvious progress, its accuracy is worthy of promotion and use.

4.3. Prediction of the Highest Value of Fund Performance by Improved POS-RBF Algorithm. Through the analysis of Figure 3, we have seen the comparison results of PSO-RBF NN and simple RBF NN algorithm for the prediction of the continuous performance of security funds. Obviously, the optimized and improved algorithm has greater advantages and greatly improves the accuracy. For the sake of further verifying program effect of PSO-RBF NN algorithm in fund performance, we take half a year as a cycle to predict the highest value of fund performance.

According to the data in Table 3, the optimization algorithm using PSO-RBF neural network can predict the trend of the highest value of fund performance, with small error with the actual results. The lowest relative error value of the five tests is 1.58%, and the average relative error is also kept within 2%. The error is small and can be widely used.

4.4. Prediction of the Highest Value of Fund Performance by Improved POS-RBF Algorithm. Different from the prediction of the highest value of fund performance, the change of the decline and the lowest value of fund is often more complicated, which also involves more influencing factors. To verify PSO-RBF NN in the most unfavorable environment of fund performance prediction, based on an example, we also predict the minimum performance of a fund in a half-year cycle for five cycles. Figure 4 is a comparative analysis of the predicted results and the actual performance. Through Table 4, we calculated the relative error value and the average value of the five tests, which are the same as the results of the above tests. The optimization algorithm using PSO-RBF also achieved good results in the prediction of the lowest value, and the average value was also controlled within 2%, which fully proves the feasibility and superiority of this research method in the prediction of fund performance.

5. Conclusions

The trend of security fund performance is generally restricted by many factors, such as politics, market environment, and business strategy. But in disorder, it can also find the hidden rules, and with the help of neural network, it can predict the sustainable trend of fund performance. For example, the RBF neural network introduced at the beginning of this paper is widely used in the financial field and has a good research method for the performance and sustainability of the fund. In this paper, after exploring the structure and workflow of the traditional algorithm, PSO is improved on its basis, and a new PSO algorithm based on RBF is obtained. In the specific study of PSO-RBF, we find that although the prediction solution of RBF is consistent with the actual numerical trend, there is a large error value, and the latest PSO-RBF algorithm can improve this point very well; no matter in accuracy and stability, there is a big breakthrough. In the prediction of the sustainable performance of security funds, the accuracy of the prediction results of the highest value and the lowest value is controlled within 2%. Generally speaking, the performance estimation PSO-RBF NN model in this paper is good, but the current research is still in its infancy. I believe that in the next in-depth research, this method will also improve its application value, which is worth popularizing security fund performance prediction model.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there is no conflict of interest.

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