The Application of Neural Network in Stock and Futures Forecasting

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Abstract—The forecasting of stock and futures markets has always been an attractive technical issue in the financial field. This paper introduces the basic principles of RBF and BP neural networks and expounds on their calculation methods in stock and futures market prediction, respectively. RBF neural network uses the three-layer network to build the prediction model of the stock market. Based on preprocessing the sample data, determining the RBF neural network center and training the output layer weight of the RBF network, it can accurately predict the stock price without changing the model and various parameters. BP neural network has been widely used in function approximation, pattern recognition, classification and data compression. It extracts 10 kinds of possibly relevant data from futures transaction data, calculates the correlation coefficient, extracts four key factors, and constructs a prediction model. It improves the calculation accuracy compared with using 10 items of data directly. Meanwhile, the paper also points out two neural networks' improvements in current use and puts forward feasible methods. These results shed light on the application of neural networks in the stock market and provided guidance for the future development and innovation of neural networks.

Keywords-Stock market; Price forecast; Neural Network; RBF; BP

1. INTRODUCTION

With the rising heat of the current stock exchange market, the increasing number of investors turn their eyes to the stock and futures transaction field. Nevertheless, due to the uncertainty of price and risk factors and the psychological factors and investment ability of investors, various auxiliary analysis methods of investment have increasingly become the spokesman of the investment industry. However, some traditional methods, e.g., technical analysis and basic analysis, either require financiers to have a more in-depth understanding of the K-line diagram

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or tangent diagram of financial data or contain relevant knowledge of multiple disciplines and influencing factors, which brings great difficulties and risks to investors' prediction of stock and futures. At this time, the advantages of neural network analysis models are highlighted. The characteristics of the neural network, such as self-processing, self-organization, self-adaptive and good fault tolerance, enable it to act on multi-factor, uncertain and nonlinear time series prediction.

Contemporarily, the neural network has made remarkable achievements in many fields, e.g., target detection, image classification, image segmentation, etc. Neural network prediction solves the problems that may be difficult to be solved by traditional prediction methods and brings dawn to stock prediction. The advantages of simple structure, fast learning speed and high fitting accuracy of the neural network also provide a great convenience for the process of prediction [1].

Researchers found that the accuracy of the neural network model in predicting nonlinear time series data is much higher than the ARIMA model. Bayogly and Bahadir compared the prediction effects of Bayesian estimation and neural network model with different standards. The results show that the prediction effect of the neural network model is better. Liu Haiyue and Bai Yanping established AR, RBF and GNN neural network models to predict the opening price, closing price, highest price and lowest price of the Shanghai stock index, compare with the actual price and analyze the error, and demonstrate the effectiveness of the three models. However, the AR model is relatively unstable, the RBF and GRNN network training speed is fast, and GRNN shows a better effect [2]. Dai H, Zhang Y and Wang D propose a prediction method called SVM in their paper, which fuzzies the commonly used data into particles for hybrid calculation [3, 4].

RBF radial basis function network is a forward neural network model with high operation speed and nonlinear mapping function. On the other hand, BP error backpropagation network is a common neural network model based on fewer neurons when the number of neurons in the input layer, hidden layer and output layer is basically the same or pyramid structure. This paper aims to introduce the application of RBF in stock trading and BP in futures trading, the basic principles and application examples of two neural network models. For applying the new analysis method in the market, based on the real stock data, this paper will use Python to write programs in line with the two network models to predict the real data.

As the basic unit of the artificial neural network, the algorithm of the neuron is not complicated. However, the complete neural network is composed of a large number of interconnected neurons and has powerful information processing ability. The function of the neural network cannot be separated from its reasonable connection mode, nonlinear processing and plastic interconnection structure. Therefore, following certain orders and rules is necessary to interconnect neurons into networks [5].

2. RADIAL BASIS FUNCTION(RBF) IN STOCK MARKET

2.1 Principle of RBF

One kind of feedforward neural network should contain input neurons, hidden neurons, and output neurons. There are only three layers and even little as one hidden layer in RBF neural network. However, it uses RBF as the basis of hidden neurons to approximate the function with arbitrary accuracy. In this case, the directly given input vector and target vector can be directly applied to the single-layer hidden space, making the learning process more efficient.

The kernel method has been highly expected in the current algorithm to summarize the general type of data and study its general laws and types. Meanwhile, RBF uses the Gaussian kernel function, which can weight the distance ratio between spatial view samples and can map the data to any dimension. Under this neural network, the Object Relational Mapping is determined along with the determination of the RBF central point, and the mapping between the hidden layer space and the output space is linear. Thus, for example, when the data is not shared in the plane, the hidden layer that plays a role redistributes and separates these two-dimensional vector mappings in the three-dimensional space (as shown in Figure 1). In the same way, this operation will map from any low dimension to any high dimension and then make indivisible data linearly separable.

- The independent variable of the hidden layer of the RBF neural network is the vector distance between the input value and the central value, and the activation degree of the activation function is positively correlated with the size of the independent variable.
- Unlike BP neural network, RBF is a neural network with "local mapping" characteristics, i.e., only a few adjustable parameters or connection weights in the local area of the neural network affect the output, which speeds up the learning speed and meets the real-time needs.
- The input-output mapping of the neural network is nonlinear, while the network output is linear for adjustable parameters. As a result, the weight of the network can be solved directly by the linear equations, which greatly speeds up the learning speed and avoids the local minimum problem [4].

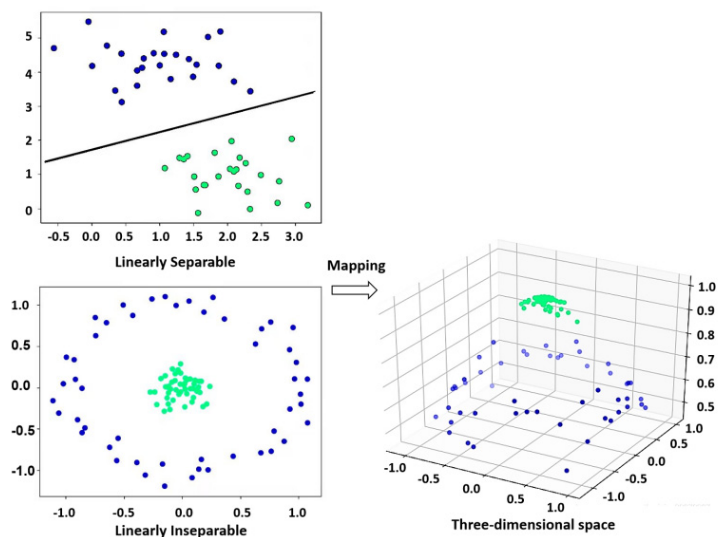

Figure 1. A sketch that disordered data in two-dimensional can be linear and separable in three dimensions

2.2 Model construction

2.2.1 Data processing

The change of stock price is nonlinear, and RBF neural network is a feedforward neural network that can linearly process the data in other dimensions in the middle layer, which improves the prediction accuracy and reduces the time cost (learning time). The nonlinear transformation from input space to output space *R* is realized by the linear combination of nonlinear basis functions. Therefore, for predicting stock data, *P* data in history needs to be used to predict *Q* data in the future, i.e., the nonlinear relationship from *RP* to *RQ* is linearly output in other dimensions.

Supposing there is a function, where p represents the stock price (opening price, closing price, highest price or lowest price), and X and Y represent the external factors that affect the price, one derives

$$P_{t+1} = f(P_{t-k,} \dots P_t, X_{t-m,} \dots X_t, Y_{t-n,} \dots Y_t) \tag{1}$$

If external factors are ignored, $P_{t+1} = f(P_{t-k,} \dots P_t)$ can be obtained.

As shown in the formula, establish an n-dimensional input and one dimensional output model for stock price prediction (as illustrated in Figure 2). Based on the historical data of the stock price in the previous "n" days, the stock price in the next day is obtained. For example, for the known "n+1" day, the stock price are P_{t-k} ,..., P_t,P_{t+1}, the input of the network is $X = (P_{t-k,} \dots P_t)^T$ and the expected output is $S = P_{t+1}$.

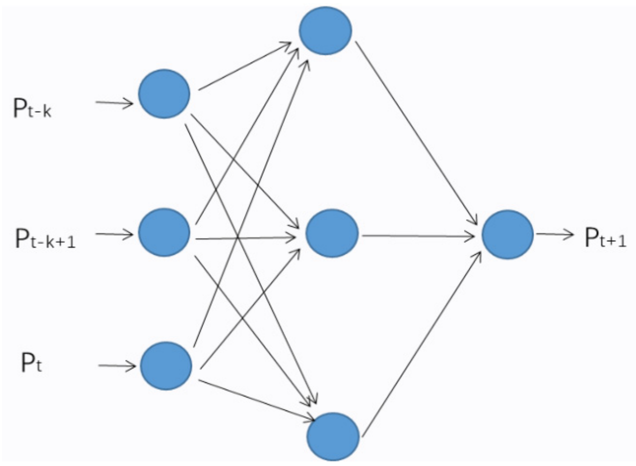

Figure 2. A sketch of the structures of neural networks

Then the training sample set of the model can be written as

$$R = \{[X_1, S_1], [X_2, S_2], [X_3, S_3]\} \tag{2}$$

where

$$[Xi,Si] = [(P_i, P_{i+1}, \dots, P_{i+n-1})^T, P_{i+n}] \tag{3}$$

2.2.2 Determination of RBF Neural Network Center

Since static RBF can only carry out the conventional algorithm and off-line learning through a large number of sample data, some academic articles propose a "dynamic adaptive learning algorithm", i.e., the online adaptive clustering learning algorithm is added based on the conventional algorithm. Thus, it does not need to take a large number of data as the cost to obtain the optimal effect [6, 7]. The algorithm is as follows:

1) The number of initialized cluster centers is 1. Initialize cluster center C1 and use it as the first training sample.
2) Classify all samples x according to the nearest cluster center
3) Calculate the average value of various samples and modify the cluster center
4) Repeat steps 2 and 3 until all cluster centers meet a predetermined threshold and the change of cluster center is less than the threshold. It can be regarded as that the cluster center does not change anymore.
5) Calculate the samples farthest from the center and the farthest distance in each sample class: if the farthest distance is greater than the predetermined threshold, increase the number of centers and initialize the new center, i.e., return to step 2; Otherwise, enter 6
6) Assign each clustering center to each RBF unit as the center of the RBF network (if you want to optimize the network structure, proceed to step 7 after learning the weight of the output layer)
7) If the weight of the output layer is equal to 0 or minimal, delete the corresponding RBF Network Center

2.2.3 Training & Observation

The experiment is based on the stock closing price data of stock in Shanghai Securities Company from January 2, 1992, to December 31, 2002, as an example. As a result, it is said that the accuracy of prediction using RBF neural network is improved, so the effect of quantitative analysis is better than that of basic analysis and technical analysis (the trend accuracy is 53.36% and 52.80%, respectively; the average error is 0.0417 and 0.0248, respectively).

Similarly, the prediction effect of the improved model is also significantly better than that before the improvement [7].

2.3 Application

In 1988, econometrician White used his technology application in the neural network to accurately calculate and predict two common stocks' daily return on investment. After long-term analysis and comprehensive learning of many training materials and samples, the calculated long-term prediction analysis results do not seem to be very ideal. However, his prediction of the company's daily inventory occupancy rate has achieved good results.

In 1990, Kimoto and other researchers of neural network technology developed the comprehensive prediction model analysis and calculation system of Tokyo Stock Exchange Price Index in Japan, mainly to comprehensively predict the long-term trend of the weighted comprehensive average stock price index of the shares listed on the Tokyo Stock Exchange, to analyze and determine the best trading opportunity for them to choose to buy and stop selling.

In 1992, Kokozaki and other professors used a neural network prediction algorithm model with 15 input variables, 2 input hidden data layers and 1 output variable to accurately analyze and predict the stock price rise and fall trend of the Japanese stock market in that year. The training samples analyzed and studied the stock price rise and fall trends, respectively. As a result, the accuracy of the method of predicting the stock price rise and fall of the Japanese stock market in that year and the direction determined by its trend is quite high. However, if there is a wrong deviation between the decisions made between the rise and fall trends, the accurate prediction ability of the neural network will be greatly weakened. However, it can still be correctly used to predict the stock price of Listed Companies in that year.

In 1996, Gencay company used the market moving average curve algorithm to apply the analysis technology as an important index for accurately analyzing and judging the information related to the purchase and sale of shares in the stock market by the neural network. When the long-term market moving average curve and the short-term market moving combination average are close to each other, A cross section of stock buying and selling information is set to avoid the wrong and accurate judgment on the information related to stock buying and selling caused by the transaction directly due to the violent fluctuation of the market share price.

In 1999, according to the data description, Pesaran and Timmermann predicted the London Stock Index in the past five years. The monthly change rate of the index predicted by neural network technology can reach 60% accuracy.

In 2001, Chungkimkwong company used the statistical data of seven enterprises in the Australian company's stock and bond market last year to analyze its performance. The average data prediction accuracy was about 48.2%.

Domestic scholars have also conducted many useful studies: In 1997, Zhang Jian and other responsible persons conducted technical research and data analysis on many stocks of four listed companies in Shanghai Shanghai Stock Exchange Group Industry - Shanghai Lujiazui, Fuhua group industry, Changchun Hualian and Shanghai Petrochemical through research and application of neural network, and proposed that the price difference between the rise and fall of individual stocks and the recent fuzzy amplification. Based on the long-term fuzzy calculation technology and analysis method, the data input and output of the company's network are analyzed and processed at the same time, and its technical effectiveness has been verified by practice.

In 1999, Liang Xia proposed a network prediction analysis method that can increase the self-defined correction and network error correction prediction functions of mobile Internet at the same time. Taking the closing price, transaction volume and transaction amount data between Shanghai Jinling and Shenda industries last year as the original statistical data, it is found that after adopting the new data calculation and analysis method, the data reliability of the network market prediction and analysis system is significantly improved compared with the BP model. Furthermore, from the mathematical perspective of nonlinear radial time curve series system prediction, Wang Shangfei and others used radial sliding window prediction technology and motion neural network prediction model based on radial basic wave function to predict a variety of curve series of IBM's China stock index, of which the combination of curve and analog number is better.

In 2001, Wu Wei and other three people used the new neural network to accurately predict the price rise and fall of China's stock market in real time. Through a large number of market numerical analysis experiments and market comprehensive data analysis, the system performance and network structure characteristics of the new neural network were specially designed, improved and comprehensively optimized. Better market prediction and analysis accuracy was obtained.

2.4 Limitations

(1) At present, the model can only predict the stock price in the next day but cannot make a rolling prediction (it can predict the next day, the third day or more in the future, which can improve efficiency and practicability)

(2) It can't make necessary inquiries to users, and when the data is insufficient, the neural network can't work (Can be more targeted and multifaceted to customers in the future)

(3) The basic characteristics of all problems are transformed into numbers, and all reasoning is transformed into numerical values for calculation. The result is bound to be the missing information.

(4) The current theory and machine learning algorithm still need to be further improved:

A hidden layer neural network's nonlinear data mapping processing ability is mainly reflected in a hidden layer basis function. Besides, the nonlinear mapping characteristics of the hidden layer basis function are mainly determined by the nonlinear mapping central node of the basis function, which is constructed by arbitrarily selecting other central nodes from a data source node. Therefore, the nonlinear mapping performance of the hidden layer neural network obviously can not achieve satisfactory technical objectives.

(5) Neural networks (e.g., RBFG) are widely used in nonlinear industrial systems sample modelling. One of the key problems is the correct selection of system sample extraction data. In the system industry's training process, the system's sample information can only be obtained by system analysis and comprehensive calculation from all operating system data actually running in the system. Therefore, effectively reducing the physical impact and system dependence of neural networks on industrial training samples is particularly important in practical industrial applications.

3. BACK PROPAGATION NEURAL NETWORK (BP) IN THE FUTURES MARKET

3.1 Principle of BP

Backpropagation (BP) is a concept put forward by scientists led by Rumelhart and McClelland in 1986. It is a multi-layer feedforward network. It consists of an input layer, hidden layer and output layer, which can realize any complex nonlinear mapping and be used to deal with nonlinear prediction problems. The structure of the BP neural network is depicted in Figure 3 [8].

The learning step of the BP neural network algorithm consists of two processes: forward propagation of information and backpropagation of error. Each neurone in the input layer receives input information from the outside and transmits it to each neuron in the middle layer. The middle layer is the internal information processing layer, which is responsible for information transformation. According to the requirements of information change ability, the middle layer can be designed as a single hidden layer or multi hidden layer structure. The last hidden layer transmits the information to each neuron of the output layer. After further processing, it completes the forward propagation processing process of one learning, and the output layer outputs the information processing results to the outside world. When the actual output is inconsistent with the expected output, it enters the backpropagation stage of error. The error passes through the output layer, modifies the weight of each layer in the way of error gradient descent, and transmits it back layer by layer to the hidden layer and the input layer. The repeated process of information forward propagation and error backpropagation is the process of continuously adjusting the weight of each layer and the process of neural network learning and training. This process continues until network output error is reduced to an acceptable level or the preset learning times.

The models of BP neural network mainly include input-output model, action function model, error calculation model and self-learning model, among which error calculation model and self-learning model are the key parts of this algorithm.

The error calculation model reflects the error between the expected output and the calculated output of the neural network, which is used to determine whether the hidden layer weight of the forward transfer is available and whether the reverse transfer error is required. Before training the network, we must give the loss function. The training process is to reduce the loss function. Here, we take the mean square error between the predicted value and the actual value:

$$E_k = \frac{1}{2}\sum_{j=1}^{l}\left(\widehat{y_j^k} - y_j^k\right)^2 \tag{4}$$

The self-learning model is the neural network's learning process, i.e., the setting and error correction process of the weight matrix W_{ij} connecting the lower node and the upper node. BP network has the learning mode with the teacher (i.e., needs to set the expected value) and the learning mode without the teacher (i.e., it only needs to input the mode). The self-learning model is:

$$\triangle W_{ij}(n=1) = h\varphi_i O_j \mathrm{a} \triangle W_{ij}(n) \quad (5)$$

Where h is learning factor; φ_i is calculation error of output node i; O_j is calculation output of output node j;

a is momentum factor.

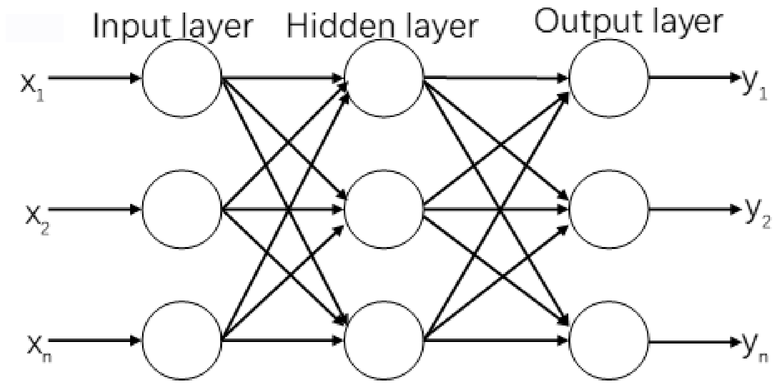

Figure 3. A sketch of BP neural networks

3.2 Processing of BP

The first step is extracting the key factors in the data of the day. The key factors are extracted from the 10 factors affecting the closing price of the next day, e.g., the daily opening price, closing price and maximum price, and the closing price of the next day is predicted by BP neural network. It can be seen from Table 1 that the relationship between the daily opening price, closing price, maximum price and minimum price and the closing price of the next day is high, indicating that these four data have a great impact on the closing price of the next day. Therefore, these four factors are extracted as the key factors.

Table 1. Pearson Correlation coefficients for various factors

	Daily opening	Daily closing	Daily maximum	Daily lowest	Daily increase	Daily amplitude	Daily general hand	Daily transaction amount	Daily turnover rate	Daily transaction times
Next day closing price	0.9886	0.991	0.9897	0.99	0.094	0.353	0.1202	0.3893	0.5694	0.2903

Subsequently, the data processing is implemented. Before forecasting, it is very important to preprocess the data. For example, before using BP neural network to predict the stock price, it is necessary to normalize the data. It has two main functions: one is to speed up the convergence speed of BP neural network and shorten the training time; The second is to measure and toughen different key factors and reduce the numerical difference. The normalization formula is as follows [7]:

$$\hat{x}_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{6}$$

Where X_{max} and X_{min} represent the maximum and minimum values in the data, respectively, according to the normalization calculation formula, the daily opening price, closing price, highest price, lowest price and the closing price of the next day are normalized, respectively.

Then, training and forecasting are applied.

1) Determination of the number of input layer nodes.

There are four key factors for futures price prediction, so the input layer should have four neurons, so the number of nodes in the input layer of the BP neural network is $n = 4$.

2) Determination of the number of output layer nodes. Since the results to be presented only have the closing price of the next day, the output layer only sets $M = 1$ output node.
3) Determination of hidden layer node number. The number of neurons in the hidden layer is generally related to the number of neurons in the input and output layers. So far, determining the number of nodes in the hidden layer is still an urgent problem to be solved. If the number of hidden layer nodes is too small, the convergence speed of the whole neural network will be slow and difficult to converge; On the contrary, if too many hidden layer nodes are selected, the topology of the neural network will be complex, the amount of calculation in iterative learning will be large, and the error may not be the best. In addition, too many hidden nodes will increase the training time.

According to the research of Charencen W Tan and Gerhard E Wittig (1993), generally, when the number of neurons in the input layer, single hidden layer and output layer is basically equal or in a pyramid structure, the operation effect of the BP model is better, as displayed in Figure 4 [9].

As for the Learning algorithm, the output algorithm of neurons in each layer (sigmoid function) is the output value from the input layer (or hidden layer) node i to the hidden layer (or output layer) j:

$$y_{ij} = \frac{1}{[1+\exp(-\sum_{i=0}^{n} w_{ij} x_i)]} \tag{7}$$

The node input value Xi, I = 1, 2,... n, indicates that the neuron has n inputs, and wij is the weight from the i-th input layer (or hidden layer) node to the j-th hidden layer (or output layer) node. When i = 0, wij indicates threshold, x1 = 1.

Regarding to weight correction. Reverse transfer from the output layer to each hidden layer. The formula is:

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j y_i + \alpha[w_{ij}(t) - w_{ij}(t-1)] \quad (8)$$

w_{ij}(t) is the connection right from neuron i (input layer or hidden layer neuron) to the upper layer neuron j (hidden layer or output layer neuron) at time t, y_i is the actual output of neuron I at time t, η is the step adjustment factor, 0< η< 1, α is the smoothing factor 0< α< 1, δj is the error weight adjustment factor. For hidden layer nodes:

$$\delta_j = x_j(1 - x_j)\sum_{k=0}^{n}\delta_k w_j \quad (9)$$

Where x_j is the actual output value of hidden layer node j. For output layer nodes:

$$\delta_j = x_j(1 - x_j)(t_j - x_j) \quad (10)$$

where t_j is the output target value, the initialization of weights and neuron thresholds is a random number distributed on (0, 1).

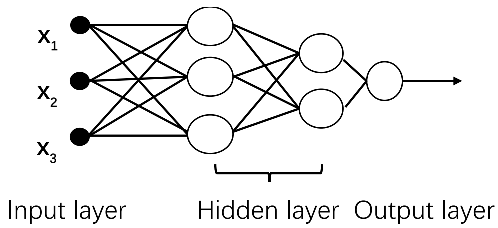

Figure 4. Pyramid hidden layer structure of BP neural network

3.3 Future guideline of BP

Although the BP network has the advantages of approaching a nonlinear mapping with arbitrary accuracy, it also has shortcomings and needs to be improved:

1) It is easy to form local minima and can not get global optimization;

2) More training times make the learning efficiency low and the convergence speed slow;

3) The selection of hidden layer nodes is lack of theoretical guidance;

4) Learning new samples during training tend to forget the old samples.

For these defects, some scholars have proposed suitable improvement schemes. At present, there are many effective algorithms:

1) Adding momentum term. When adjusting the weight, the standard BP algorithm only adjusts according to the gradient descent direction of the error at time t without considering the gradient direction before time t, making the training process vibrate and the convergence speed slow. To improve the speed, a momentum term can be added to the weight adjustment formula.

2) Introducing the steepness factor. There is a flat area on the error surface. After the adjustment enters the flat region, try to compress the net input of the neuron and make its output exit the saturation region of the transfer function to change the shape of the error function and make the adjustment out of the flat region. The specific way to realize this idea is to introduce a steepness factor into the original transfer function.

3) Adaptive learning rate. It can be seen from the error surface that the learning rate is too low in the flat area, which increases the number of training, i.e., it is desirable to increase the learning rate. On the other hand, the learning rate is too high in the area where the error changes sharply. Because the rope skipping amount is too large, it crosses the narrow place, and there is vibration during training, which increases the number of iterations. To accelerate the convergence process, a better idea is to adaptively change the learning rate to increase when it is large and decrease when it is small [10].

4. CONCLUSION

This paper investigates the RBF and BP network and concludes that the RBF has the characteristics of local mapping. In other words, the variables and weights of its hidden layer only affect the local output values nearby. This is different from many neural networks, such as the BP network. They map all the input values to the hidden layer and then map all the hidden layer data to the output layer. Hence the operation efficiency will be reduced. RBF model overcomes this shortcoming and adopts a local optimal algorithm to greatly speed up the running speed. In the meantime, the process from input to output of this neural network is nonlinear as the change of stock market value. It can meet the condition of mapping data from low dimension to high dimension to be divided for calculation. In addition, as political, economic and other multiple factors have a greater impact on the stock market in our country, the internal laws are relatively complex. Therefore, more regulatory factors need to be added to the model in the future.

Another neural network BP model mentioned in this paper has the characteristics of error feedback. It mainly introduces the error calculation and self-learning part and indicates the function used in the algorithm to calculate the error and the function in the self-learning algorithm. Based on analyzing the opening price, closing price, and maximum price of Huayi Brothers on a certain day and calculating their correlation coefficients with the next day's closing price, four parameters with high correlation are determined and normalized. From the final prediction results, the model combining BP network and correlation number is obviously more accurate. Generally, it is difficult to set the number of neurons in the middle layer in the operation of a neural network.

As for the improvement of the two neural networks, the "dynamic adaptive learning algorithm" of RBF is suitable for non large and constantly updated data. LRBF and RBFG are also improved algorithms for RBF. According to the improvement of BP, an evolutionary scheme is proposed to increase the momentum term, accelerate the convergence speed, introduce the steepness factor and adjust the learning rate. Through these purposeful optimization schemes, the efficiency of the algorithm and the accuracy of prediction are improved. These results offer a guideline for using various neural networks to predict various information of the financial market.

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