Stock Price Trend Analysis based on BP Neural Network

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Abstract. Stock price prediction is important for investors to make investment decisions. This paper applies artificial neural network to stock forecasting, establishing a five-layer BP neural network model to predict the closing price of two stocks, the Shanghai Pudong Development Bank and China Fortune Land Development, in the empirical analysis. The results show that the model can effectively make prediction on the stock closing price and the BP neural network with three layers is feasible and effective to assist making investment decisions.

Keywords: BP Neural Network; Python; Stock Prediction.

1. Introduction

The stock was born under the market economic system, and has far-reaching significance for the prosperity of the market economy and the healthy development of the national economy. As China continues to enter the reform of the deep-water area, the reform of the financial sector is also gradually deepening. Therefore, financial reforms such as capital financing, social wealth redistribution, optimization of resource allocation, and discovery of financial asset prices through the stock market play an important role. In addition, the greater the risk of investment, the greater the risk of how to establish a stock market forecasting model with relatively high accuracy and speed of operation, which has great theoretical significance and practical application value for financial investors.

As the relevant theories of securities investment continuing develop, some scholars apply this theoretical knowledge to the actual stock investment operations, and find many ways to predict the stock market. Although these methods are recognized in forecasting and investment, the stock market is a very complex nonlinear system, which is influenced and intervened by many uncertain factors. The complexity and variability of the stock system itself determines that stock forecasting is a highly complex research task, and its main performance lies in the nonlinear fluctuation characteristics of stock prices [1], [2]. However, no matter which forecasting method is used for forecasting the stock market, a large amount of data is indispensable. As a result, the stock price forecast is extremely demanding on the algorithm, and the effect of using the existing stock forecasting method to predict the stock price is not satisfactory.

In recent years, with the development of artificial intelligence and computer professional software, many new methods have emerged in stock price forecasting. Among them, neural networks have good performance in nonlinear approximation and comprehensive processing of complex information. Their self-learning and self-adaptation characteristics can overcome the limitations of common prediction methods. Therefore, neural networks are leading in the field of artificial intelligence, and have been widely applied. Hence, using neural networks to predict stock prices has a unique advantage, which can effectively overcome the problem of highly nonlinear stock prices.

BP neural network is a mathematical model that simulates the structure of human brain neural network and has certain predictive function. Because of its strong self-learning ability, self-adaptive ability and fault tolerance, it becomes a more suitable stock forecasting method. Based on this, this paper proposes a stock price forecasting model based on BP neural network. The basic idea of the model is that the learning process consists of two processes: the forward propagation of the signal and the back propagation of the error. In the case of forward propagation, the sample consisting of various factors affecting the closing price of the stock is transmitted from the input layer, processed by each hidden layer, and then transmitted to the output layer. If the actual output of the output layer is different from the expected output (true closing price), it will be transferred to the backpropagation phase of the error. Error backpropagation is to spread the output error back to the input layer through the hidden layer in some form, and distribute the error to all the units of each layer, so as to obtain

the error signal of each layer unit. The layer of signal forward propagation and error backpropagation of the various layers for weight adjustment process is repeated. The process of constant adjustment of weights is the learning and training process of the network. This process continues until the error in the network output is reduced to an acceptable level or to a predetermined number of learnings.

2. Related Works

Since the birth of the stock, many scholars at home and abroad have actively participated in the stock market forecasting research. They have continuously developed more forecasting methods based on previous experience, including extensive fundamental analysis and technical analysis [3], [4]. However, the stock market is a complex and variable nonlinear system, and its description, analysis and prediction complexity are extremely high. Therefore, further research is needed to obtain more accurate prediction results.

Charles is the founder of the Dow Jones Index. The Dow theory of he proposed is considered as the basis for the study of the market economy in the early twentieth century. Richard studied the K-line chart to find out the pattern of the ups and downs of stocks. In the wave theory, the form of price trends appearing on the market is represented by some forms that are repeated. Later, there are many methods that rely on graph analysis for technical analysis [5-8]. Most of these methods require the operator to have rich investment experience and relevant knowledge reserves, in order to predict the stock market up and down according to the data in the chart. In order to predict the stock market effectively for a long time, the researchers combined chaos theory and traditional analysis methods, making the prediction method of nonlinear systems take a new step [9]. Le Baron is an American scholar who discovered in 1989 that there were random irregularities in the sequence of stock closing prices [10]. By observing the structure of the chart, the scholars and other people found the chaotic phenomenon in the historical data of the stock, and used the wavelet theory to predict the data processed by the dynamic system. Since the 1990s, with the development of artificial intelligence, the use of artificial intelligence to predict the stock market has become the focus of investors' research [11]. The emergence of neural networks has accelerated the development of intelligent technology, and scholars are increasingly keen to combine economics with neural networks. In the late 1980s, scholar White used artificial neural networks to predict the stock returns. Because the algorithms used at the time were vulnerable to local minimum defects, the accuracy of prediction results was low [12]. In 1990, scholar Kimoto developed a Tokyo stock price index system based on neural network algorithms combined with statistical theory [13]. In 1992, scholar Baba studied the rising and falling trends of the stock market based on the neural network algorithm. The stock market evaluation standard was used as the input variable to predict the stock price, and the accuracy of the forecast result was not stable [14]. In 1996, scholar Gencay compared the prediction effects of neural network algorithm and linear regression model with graph analysis method respectively, and proved the superiority of neural network prediction [15].

China's stock market has been established relatively late. Due to the particularity of China's policies and national conditions, the domestic stock market is more complex and less stable than other developed countries [16], [17]. Therefore, foreign stock market forecasting methods cannot be put into the Chinese stock market. The stock market forecasting methods commonly used by domestic scholars are mainly a hybrid forecasting method that combines neural networks with other intelligent algorithms [18], [19]. Ye Zhongxing and other scholars developed a new cognitive system using neural network algorithm based on fuzzy theory. The simulation results show that the prediction accuracy is higher [20].

On the whole, domestic scholars' research on the stock market is mainly focused on the field of neural networks. However, the factors affecting the stock market are various, including the domestic and international economic situation, the industry situation and the individual will of investors. The cross-effects of these factors have created more complicated problems. How to solve this complicated problem has become a hotspot of numerous researchers.

3. BP Neural Network Model

The BP (Back Propagation) network was proposed by a group of scientists led by Rumelhart and McCelland in 1986. It is a multi-layer feedforward network trained by error inverse propagation algorithm and is one of the most widely used neural network models. The BP network can learn and store a large number of input-output mode mapping relationships without first revealing mathematical equations describing such mapping relationships. Its learning rule is to use the steepest descent method to continuously adjust the weights and thresholds of the network through backpropagation to minimize the sum of squared errors of the network. The BP neural network model topology includes an input layer, a hide layer, and an output layer.

The artificial neural network model has experienced many years of ups and downs, and it ushered in a high tide of research in the 1980s. In 1982, biologist Hopfield proposed a single-layer feedback network: Hopfield Network. The concept of feedback mechanism and energy function are introduced into the network, which promotes the development of artificial neural network. The continuous Hopfield network can effectively solve the optimization problem, and the discrete Hopfield network can be used to solve the problem of associative memory. Researchers such as Hinton introduced a stochastic mechanism in the Hopfield network, and proposed the Boltzmann Machine model, which contains a hidden layer and a visible layer. All neurons are symmetrically connected, and the model has strong ability of unsupervised learning. In 1986, researchers such as Rumelhart and Hinton proposed the application of Back Propagation (BP) to the training of neural network models which can be reversed by error. The network weight parameters are updated so that the artificial neural network can learn some statistical laws from a large number of training samples. Then, the leared laws can be used to predict unknown things. The proposed method solves the problem of artificial neural network training difficulties. From then on, another wave of artificial neural networks has emerged. Since then, self-organizing networks and Support Vector Machine (SVM) models have emerged. Below we use a simple three-layer neural network to explain the structure of the traditional neural network and the detailed process of the BP algorithm:

The same as the general artificial neural network, the neurons that make up the BP network are still neurons, and the network model is shown in Figure 1:
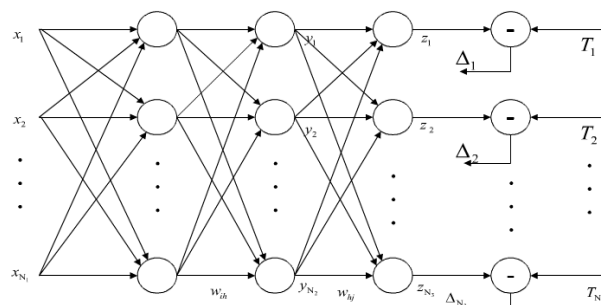

Figure 1. BP neural network model

For a neuron, its network input can be expressed as:

$$\text{net} = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n, \tag{1}$$

where $x_1, x_2, \cdots, x_n$ represent the inputs of the neuron, and $w_1, w_2, \cdots, w_n$ are the connection weights.

The output of this neuron is:

$$y = f(\text{net}) = \frac{1}{1 + e^{-\text{net}}}, \tag{2}$$

Where f is the Sigmoid activation function.

The standard BP algorithm is a learning algorithm based on the gradient descent method. The learning process is achieved by adjusting the weights and thresholds to minimize the mean square error of the output expected value and the actual output value for the neural network, but it only uses the mean square error. The function's information on the first derivative of the weight and the threshold makes the algorithm have the drawbacks of slow convergence and small localization.

The training process of the algorithm is mainly divided into the following parts:

(1) Network weight initialization. Before the network training begins, the connection weights between all the neurons in the network are first initialized, and the ownership is randomly assigned or assigned according to some statistical law.

(2) The signal propagation forward in the network. The training samples are input at the input layer of the network, and the signals are propagated backward through layers. The output of each neuron in each layer is calculated until finally passed to the output layer to obtain the entire network output. The operation of each neuron is to weight all the inputs of the previous layer, and then get the output of the neurons through a nonlinear activation function (usually the Sigmoid function). The hidden layer output can be expressed as:

$$\begin{cases} h_1 = F(w_{11}x_1 + w_{21}x_2 + ... + w_{i1}x_i) \\ h_2 = F(w_{12}x_1 + w_{22}x_2 + ... + w_{i2}x_i) \\ ... \\ h_j = F(w_{1j}x_1 + w_{2j}x_2 + ... + w_{ij}x_i) \end{cases} . \tag{3}$$

The output layer can be expressed as:

$$\bar{y} = F(w_1h_1 + w_2h_2 + ... + w_jh_j) . \tag{4}$$

Where $\bar{y}$ is the actual output of the network, F is a nonlinear excitation function, such as Sigmoid or Tanh. Taken together, the forward propagation phase calculates the output of each neuron on each layer from the sample input until the output of the entire network is calculated.

(3) Error back phase. First, the error of the output layer is calculated according to the actual output of the network in the forward propagation phase $\bar{y}$ and the ideal output (given label value) y given in the training data set (the square sum of the difference between the actual output and the ideal output is used as the error here):

$$E = \frac{1}{2}(y - \bar{y})^2 . \tag{5}$$

Then the original problem is transformed into the problem of minimizing the error function. The gradient descent method is used to solve the optimization problem, and the weight of the hidden layer to the output layer is updated:

$$\begin{aligned} w_{ij} &= \frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial h_j} \cdot \frac{\partial h_j}{\partial w_{ij}} \\ &= [(y - \bar{y}) \cdot (-1) \cdot F'(w_1h_1 + w_2h_2 + ... + w_jh_j) \cdot w_j] \\ &= -(y - \bar{y}) \cdot F'(w_{1j}x_1 + w_{2j}x_2 + ... + w_{ij}x_i), \\ w_{ij} &= w_{ij} - \eta_2 w_{ij} \end{aligned} \tag{6}$$

Among them, the calculation of the output layer error to the weight derivative of the input layer to the hidden layer, using the chain law of derivation. Specifically, we first obtain the partial derivative of the output error to the hidden layer output, and then find the hidden layer output to the input layer to the hidden layer.

(4) Check if the termination indicator is reached. Repeat the above steps (2) and (3), continuously update the network weights through the training data, and train the network parameters until the termination condition is reached. At this point, the network training ends and the trained neural network model is obtained. Among them, we generally specify the number of weight update or the

range of error reduction as the network training termination indicator. After the indicator is reached, the training ends.

Most of the traditional artificial neural networks only include the input layer, the hidden layer and the output layer. The number of layers in the network is often shallow, the network structure is simple. As a result, the ability to express complex functions is limited, and the problems that can be solved are relatively simple.

4. Experimental Simulation and Analysis

4.1 Experimental Parameters

(1) Determination of variables. This experiment takes the 21 variables of today's opening price, today's highest price, today's lowest price, today's trading volume, KDJ index, RSI indicator, PSY index, WR index, stage strength index, stage weakness index, and market index as input variables. Take the today's closing price as the output variable. The input variables contain the stock information and reflect the market information. First, they include both the price information and the volume information. Second, they contain both recent information and historical long-term information. Third, they contain both trend information and strong and weak information. Therefore, in general, the input variables selected in this paper can more accurately reflect the factors affecting the stock trend, thus improving the accuracy of the experiment.

(2) Normalized processing. In order to eliminate the difference of the order of magnitude between the data of each dimension and avoid the phenomenon that the model prediction error is large due to the large difference in the magnitude of the dependent variables, the input and output variables are normalized by the maximum and minimum methods.

(3) Determination of the number of hidden layer nodes. There is a great correlation between the number of hidden layer nodes in the BP network and the prediction accuracy of the BP network. When the number of nodes is too small, the training ability of the neural network will be weak, and accurate prediction cannot be completed. When the number of nodes is too large, the neural network training time will get longer and the network may be over-fitting. Therefore, choosing the appropriate number of nodes can maximize the performance of the BP network. However, there is no unified standard to determine the number of nodes in the hidden layer. Therefore, after many experiments and multiple comparisons, the hidden layer nodes are finally determined. The numbers are 32, 64, and 32, respectively.

(4) Determination of the BP network structure. This paper uses tensorflow deep learning toolbox in Python to perform simulation experiments. The BP neural network is created with three hidden layers. The network hidden layer neuron transfer function and the output layer neuron activation function are both Rectified Linear Unit (ReLU). The optimization function is AdamOptimizer. The learning rate is set to 0.001. The maximum epoch of training is 1000. The batchsize is set to 128.

(5) Data selection. For the sake of generality, Shanghai Pudong Development Bank (SPDB, 600000) and China Fortune Land Development (CFLD, 600340) are selected as experimental subjects. 379 samples are selected between December 6, 2017 and June 28, 2019. 36 sets of transaction data from July 1, 2019 to August 19, 2019 are used for test verification. In addition, in order to cancel the influence of stock ex-dividend and ex-dividend, this paper adopts transaction data after post-recovery.

4.2 Experimental Results and Analysis

Using the constructed BP neural network to train 379 data samples from the selected Shanghai Pudong Development Bank (SPDB, 600000) and 379 data samples from China Fortune Land Development (CFLD, 600340), the training error was reduced to 0.005. Tables 1 and 2 show the closing of SPDB and CFLD stocks predicted by our method, respectively. From the perspective of the predicted output and the expected output, the BP network has achieved the judgment of the stock price to a certain extent. The error is basically controlled within 1.2%, and the experimental accuracy is satisfactory.

Table 1. Output and Error of Partial BP Network Test Samples (SPDB)

Date	GroundTruth	Prediction	Relative Error
2019/07/01	11.71	11.8368454	1.08%
2019/07/02	11.61	11.64183331	0.27%
2019/07/03	11.56	11.53853989	-0.19%
2019/07/04	11.62	11.60279274	-0.15%
2019/07/05	11.57	11.56310654	-0.06%
2019/07/08	11.36	11.40886021	0.43%
2019/07/09	11.37	11.36026669	-0.09%
2019/07/10	11.35	11.34278488	-0.06%
2019/07/11	11.4	11.40107441	0.01%
2019/07/12	11.52	11.49240971	-0.24%
2019/07/15	11.5	11.41179943	-0.77%
2019/07/16	11.55	11.53372288	-0.14%
2019/07/17	11.48	11.4466362	-0.29%
2019/07/18	11.49	11.44694042	-0.37%
2019/07/19	11.58	11.56555653	-0.12%
2019/07/22	11.48	11.45567417	-0.21%
2019/07/23	11.49	11.40966511	-0.70%
2019/07/24	11.59	11.57241917	-0.15%

Table 2. Output and Error of Partial BP Network Test Samples (CFLD)

Date	GroundTruth	Prediction	Relative Error
2019/07/01	32.86	32.97410965	0.35%
2019/07/02	33.16	33.04178238	-0.36%
2019/07/03	32.82	32.66158295	-0.48%
2019/07/04	33.39	33.31855011	-0.21%
2019/07/05	32.72	32.47843552	-0.74%
2019/07/08	31.9	31.65259361	-0.78%
2019/07/09	32.01	32.17936325	0.53%
2019/07/10	31.57	31.17302704	-1.26%
2019/07/11	31.76	31.62100983	-0.44%
2019/07/12	30.4	30.27741814	-0.40%
2019/07/15	30.36	30.23518372	-0.41%
2019/07/16	30.76	30.91261482	0.50%
2019/07/17	30.44	30.57096481	0.43%
2019/07/18	29.99	29.76117516	-0.76%
2019/07/19	30.88	30.87283134	-0.02%
2019/07/22	30.67	30.72370529	0.18%
2019/07/23	30.18	30.26400185	0.28%
2019/07/24	30.53	30.20446205	-1.07%

Figures 2 and 3 visualize the comparison of SPDB and CFLD stock closing price predicted by the proposed method and real closing price. It can be seen that the BP network has better prediction ability after training. The error of the BP neural network used to predict the stock closing price is small, and the network generalization ability is better. Therefore, the BP network can be realized to a certain extent under certain conditions judging the stock price trend.
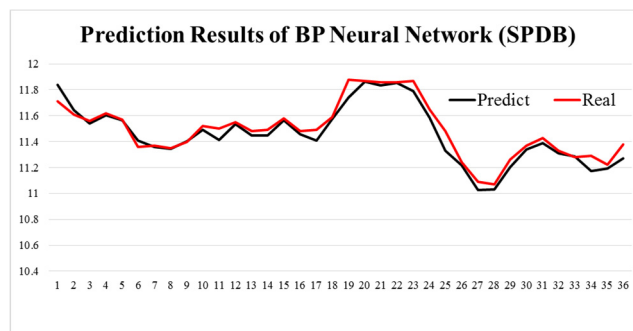
Figure 2. Prediction Results of BP Neural Network (SPDB)
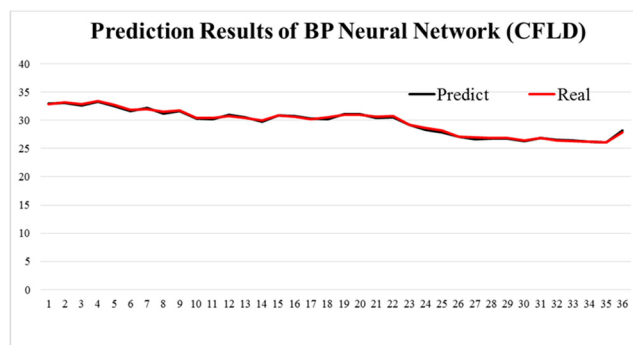

Figure 3. Prediction Results of BP Neural Network (CFLD)

Figure 4 and Figure 5 show the changes in the loss during the training process. It can be seen that the proposed method can basically converge when the training discussion reaches 400 epoches, and achieve a better forecast of the closing price of the stock.
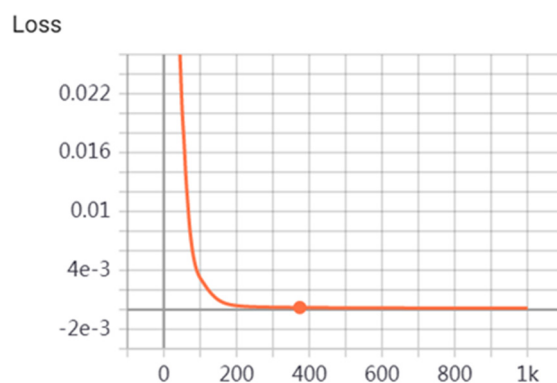

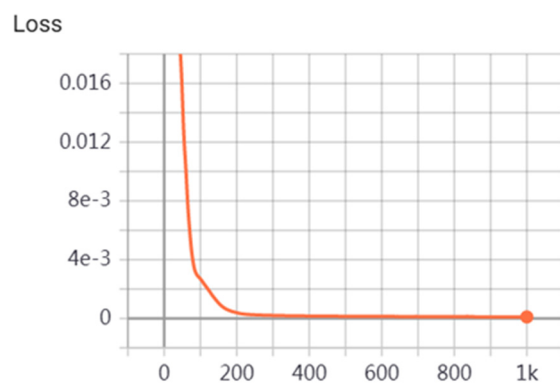Figure 4. Changing of training loss (SPDB)

Figure 5. Changing of training loss (CFLD)

5. Conclusion

Because BP neural network has strong self-learning ability, self-adaptive ability and fault tolerance, it can predict the stock price trend to some extent under certain conditions. However, since the stock market is a complex system with unstable nonlinear dynamic changes, and the variables affecting the stock price cannot be completely determined. The stock price prediction that can be realized by simply relying on the BP network is limited, and other mathematical methods need to be integrated to improve the prediction accuracy.

References

[1]. Deboeck G J. Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic financial Markets[M]// Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic Financial Markets. John Wiley & Sons, Inc. 1994:54-61.

[2]. Sentiment analysis on social media for stock movement prediction[J]. Thien Hai Nguyen, Kiyoaki Shirai, Julien Velcin. Expert Systems with Applications. 2015 (24).

[3]. Nair B B, Kumar P K S, Sakthivel N R, et al. Clustering stock price time series data to generate stock trading recommendations: An empirical study[J]. Expert Systems with Applications, 2017, 70:20-36.

[4]. Li Q, Chen Y, Jiang L L, et al. A Tensor-Based Information Framework for Predicting the Stock Market[J]. Acm Transactions on Information Systems, 2016, 34(2):11.

[5]. Chi, W. (2018, March). Forecasting Stock Index Based on BP Neural Network Algorithm. In 2018 International Conference on Mechanical, Electronic, Control and Automation Engineering (MECAE 2018). Atlantis Press.

[6]. LAPEDESA, FARBERR. Genetic data base analysis with neyralnets[C]. IEEE conference on Neural Information Processing Systems-Natural and synthetic,1987.

[7]. Kohara, K., Ishikawa, T., Fukuhara, Y., & Nakamura, Y. (1997). Stock price prediction using prior knowledge and neural networks. Intelligent Systems in Accounting, Finance & Management, 6(1), 11-22.

[8]. Charkha, P. R. (2008, July). Stock price prediction and trend prediction using neural networks. In 2008 First International Conference on Emerging Trends in Engineering and Technology (pp. 592-594). IEEE.

[9]. Cheng, Y. R., & Guo, S. B. (2003). Stock price prediction based on analysis of chaotic time series. Journal of University of Electronic Science and Technology of China, 32(4), 469-472.

[10]. G. Vrckonik, S. Haykin. Classing Impulse Radar Waveforms using Principal G. Vrckonik, S. Haykin. Classing Impulse Radar Waveforms using Principal.

[11]. Lawrence, R. (1997). Using neural networks to forecast stock market prices. University of Manitoba, 333.

[12]. H.White. Economic prediction using neural networks: the case of IBM daily stock returns[C]. Neural Networks. IEEE International Conference on, 1988, 2(6):451-458.

[13]. Lu, X., Chen, Y., & Li, X. (2017). Hierarchical recurrent neural hashing for image retrieval with hierarchical convolutional features. IEEE Transactions on Image Processing, 27(1), 106-120.

[14]. N. Baba. M. Kozaki, An intelligent forecasting system of stock price using neural networks[C]. Neural Networks, 1992 IJCNN, International Joint Conference on, 1992, V01. 1. 371-377.

[15].   G. Ramazan. Non-linear Prediction of Security Returns with Moving Average Rules[C]. Journal of Forecasting, 1998, V01. 15. 165-174.

[16].   Jovina Roman, Akhtar Jameel. Back Propagation and Rcurrent Neural Networks in Financial Fnalysis of Multiple Stock Market Returns[J]. Proceeding of the 29th Annual Hawaii Intenation Conference on System Sciences. Hawaii, USA, 1996, 1:454-460.

[17].   Lakhmi Jain, Anna Maria Fanelli. Recent Advances in Artificial Neural Networks Design and Applications[J]. Florida, USA, The CRC Press, 2000, 1:34.

[18].   Yu F, Xu X. A short-term load forecasting model of natural gas based on optimized genetic algorithm and improved BP neural network[J]. Applied Energy, 2014, 134(134):102-113.

[19].   Abu-Mostafa Y S, Atiya A F, Magdon-Ismail M, et al. Introduction to the special issue on neural networks in financial engineering[J]. IEEE Transactions on Neural Networks, 2002, 12 (4):653-656.

[20].   Panapakidis I P, Dagoumas A S. Day-ahead electricity price forecasting via the application of artificial neural network-based models[J]. Applied Energy, 2016, 172:132-151.