Short-term Prediction of the CSI 300 Based on the BP Neural Network Model

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Abstract. In this paper, BP neural network is adopted to predict the Shanghai-Shenzhen 300 Index (CSI 300) during a short period of 60 days (beginning from March 7th, 2018), results of which are used to determine the prediction effect of the BP neural network model on CSI (China Securities Index) 300. In addition, the present study explores the prediction effect of the BP neural network during different time periods by grouping predicted results according to the length of time. It is found that the BP neural network model performs well in predicting the CSI 300. The prediction results reveal that the price would overall decline, the fluctuation frequency would be small, and the price fluctuations would be small. Comparison between the groups during different time periods shows that prediction during a time period of less than 20 days or more than 50 days incurs larger errors, the prediction during a time period of 30 to 40 days is more accurate, and predictions errors increase sharply during the time period of more than 50 days.

1. Introduction

With the rapid development of the market economy, the stock market has attracted more and more attention and an increasing number of people choose to invest in the stock market. However, since the stock market is a very complex and volatile system which is subject to many factors such as macroeconomic environment, market conditions, etc., it often causes investors to suffer loss. Therefore, there is an urgent need to find an effective analysis method to improve returns and reduce risks; and predicting the fluctuations and trends of the stock market prices has become an important research direction. The CSI 300 is the first equity index jointly launched by the Shanghai Stock Exchange and the Shenzhen Stock Exchange with the aim to reflect the price fluctuations and performance of China’s A-share market, which is designed for use as performance benchmarks and as basis for derivatives innovation and indexing.

The significance of this research lies in two aspects. On the one hand, the theoretical significance of this study is that it further expands the research on CSI 300. Particularly, the abnormal fluctuations of stock prices usually disrupt the normal production and consumption of enterprises and residents, which in turn affects the development of the entire economy and undermines the market environment. Therefore, CSI 300 has gradually attracted the attention of society and scholars. This paper predicts stock prices, provides new materials for the economic research of the stock market, and especially provides a new prediction method for the stock market. Besides, the effect of the BP neural network in predicting the stock market is also explored, especially the relationship between prediction accuracy and the length of prediction time period. On the other hand, the practical significance of this research is to provide investors with a new possible analytical method which helps them make good investment
decisions, thus improving returns and reducing risks. The research ideas and research methods of this paper are in line with the actual stock price fluctuations, which can be directly used in reality and extended to other studies.

2. Literature Review

In recent years, the research on predicting stock prices has been continuing, with new prediction methods having been proposed and the old theory been gradually improved.

Traditional research on stock prices mainly relies on simple mathematical models. Initially, simple linear models such as autoregressive models and sliding average models were used. However, as the research deepens, the large amount of noise contained in the stock data and the uncertainties of many factors gradually expose the limitations of the original prediction models. Therefore, scientists have proposed nonlinear prediction models, such as neural networks and support vector machines.

In recent years, with the rapid development of artificial intelligence, deep learning has achieved great success in many fields. And researchers have tried to apply deep learning to the prediction of stock market prices. Some basic methods for predicting stock prices are reviewed as follows.

Time series analysis refers to the method of predicting the trend of stock fluctuations by establishing a model of stock prices and stock market index and time series correlation, such as the Auto-Regressive Moving Average Model (ARMA). Time series analysis is mainly divided into two types, univariate and multivariate. The univariate model is more suitable for short-term price forecasting in the stock market, while the multivariate model is more suitable for long-term stock market forecasting. The advantage of time series analysis mainly lies in its highlighting the role of time in prediction, its relatively simple modeling process, and its high accuracy for short-term prediction. However, it also has disadvantages. Since time series analysis highlights the role of time factor but does not consider specific external factors, it usually incurs large errors when there is a big change in the external environment. Therefore, time series analysis performs better in short-and medium-term prediction. Especially in the stock market, change in external factors is more likely to happen during the longer time periods. Besides, since external changes exert great influence on the stock market, considering the time factor but neglecting external factors will lead to large deviations in prediction [1].

Statistical forecasting refers to the method of predicting stock prices by using the models fitted by regression curves, autoregressive curves, mixed regression curves; and these curves are constructed by the use of the least square method. These models have a solid foundation in mathematical theory and are therefore widely applicable, which have developed very rapidly in recent years. For example, generalized linear models not only broaden the discussion of classical linear models but also further expand the theory of regression analysis, thus having promising application prospects. However, since statistical forecasting requires data to meet certain preconditions which are often difficult to meet in practice and the weights of different types of data are not divided (meaning all dependent variable weights are the same), this method often causes errors in prediction [2].

Grey forecasting is a method of system prediction involving uncertain factors. Specifically, there is an uncertain relationship between the independent variables and the dependent variables in the system; and a grey forecasting model is established to predict data after these factors are correlatively analyzed and the variation law between the independent variables and dependent variables in the system is determined. The advantage of grey forecasting lies in that it does not require a large number of samples or regular distribution of the samples, and it possesses high accuracy in short-term, medium-term and long-term prediction. Nevertheless, the grey forecasting method is more suitable for predicting when the data meets certain characteristics, such as population prediction and sales forecast. In contrast, when the data reveals great volatility and randomness, the models established for prediction often generate unsatisfactory results [3].

Combination forecasting refers to predicting data by the use of new models combining two or more different algorithms. While some events can be predicted by different prediction methods, the premise of each prediction method is different. Therefore the prediction results generated are different, and the accuracy of these results is also different. Besides, these prediction methods possess their own
characteristics in terms of data processing and various standards, which can all be derived from various angles. In practice, however, the data that needs to be predicted often does not exactly conform to the premise of each prediction method, thus resulting in large errors in the prediction results. A more reasonable approach is to combine different prediction methods in various ways, so that the advantages of each prediction method can be fully utilized, and prediction accuracy can be improved. The combination forecasting method is suitable for more complex prediction problems. However, when combination forecasting is employed, it is necessary to select the optimal model for the problem to be solved, and to consider the weight of different models combined [2].

Other main forecasting methods include market research, qualitative analysis methods such as expert evaluation and forecasting, and quantitative methods such as Markov chain [4].

Since the beginning of the 20th century, artificial intelligence has attracted numerous scholars both at home and abroad, and has achieved great breakthroughs. In particular, the neural network algorithm, a simple simulation method of the human brain, is an advantageous tool for discovering the secrets of artificial intelligence. Through long-term research, we have achieved an epoch-making leap in neural networks and applied it in various fields. In finance, many researchers have conducted neural network-related research and combined it with practice. The earliest research of such can date back to 1988 when White used neural networks to predict the daily return of IBM common stock. However, after training the sample, he found that neural networks generated unsatisfactory prediction effect. He thought that it was very likely that the neural network couldn’t jump out of the local minimum and thus demonstrated imperfect prediction capacity [5]. Later, researchers such as Kimo. Asakawa Yoda and Takeoka developed a stock forecasting model TPOIX in 1990 by using neural networks to predict the weighted average index of the Tokyo Stock Exchange. Specifically, the forecasting model was mainly used to find the best time for investors to buy and sell stocks; and the results concluded that the artificial neural network prediction model was significantly better than the weighted average index model [6]. In 1992, Baba and Kozaki used a neural network model employing 15 factors as input variables, 2 hidden layers, and 1 output variable to predict the rise and fall of Japanese stock prices. The training samples were divided into rising and falling types and the prediction of price fluctuations trend was quite accurate. However, if there appeared a learning error, the neural network model performed poorly in prediction. In fact, although their research results were not that accurate, they provided a new research direction for future studies. Their research inspires later scholars that it is more practical to use neural networks to directly predict the trend of stock prices instead of forecasting the exact stock prices [7]. In 1996, Jovina Roman and his colleagues explained the use of neural networks in economic-related fields such as portfolio investment and stock price forecasting. Shaun-inn Wu and his colleagues combined traditional stock forecasting models with neural network algorithms, which improved the overall forecasting accuracy [8]. In 1999, Pesaran and Timmermann adopted neural network model to predict the trend rate of the stock index every month of FTSE 100 index for the past 25 years, and achieved an accuracy of about 60% [9]. In 2000, Rodrigues and other scholars established a model combining feedforward artificial neural network and moving average. By predicting the Spanish stock market index, the results showed that the stock returns predicted by the model was much higher than those obtained after purchase [10]. In 2001, Chung Kim Kwong used the neural network model to predict the stock prices of seven large listed companies in the Australian stock market and achieved an average correct rate of 48.2% [11]. In 2003, the G. Peter experiment showed that besides being more accurate than the ARIMA model in prediction, the neural network algorithm model can also handle complex scatter data changes that are not linearly distributed [12].

Since the new century, neural networks have been researched a lot in terms of predicting the stock market. A. murat o Bayogly and Ismet Bahadir selected 215 past stock market trading data to compare the neural network and Bayesian algorithm in stock forecasting. After comparing these stock market data based on past experience, they found that both methods were applicable, but the neural network model possessed significantly higher accuracy. LuCJ believed that the data in the stock market was very complicated, involved much noise, and its trend changed more over time. He tried to remove noise using a completely independent component, and then proposed a neural network-based model to predict stock...
movements. He first created an independent component and then used it to determine the independent component and generate independent components, and finally deleted certain data to generate new components. The newly created independent component treated the data free from abnormal points as a new property of the neural network model. The model used the opening price of the Nikkei 225 Index to predict the subsequent stock prices. The results showed that the new algorithm proposed by Lu CJ was better than the model composed of wavelet denoising technology and the neural network. However, this study did not make a detailed and further study of the internal parameters and hidden layer structure of the neural network [13]. Alhaj A M used BP neural network to analyze the prices of Jordan stocks. After comparing the prediction of the statistical analysis method and the BP neural network, he found that the BP neural network model possessed higher prediction accuracy [14].

Arnold F. Shapiro integrated rough set, neural network and genetic algorithm to analyze time series separately and construct a combined model for data analysis and prediction. In this model, the strengths of each method were combined, while their shortcomings were complemented. However, this study only analyzed the influence of each method on the combined model alone, but failed to directly reflect whether such a model was really effective [15].

Murat used the neural network algorithm to process TKC stock data. The input vectors selected had different attributes, such as trends, patterns, and volatility. The results showed that the neural network prediction model was more efficient than previous models and could be used to predict short-term stock returns and other financial product returns. However, there were different degrees of non-objectivity in the process of prediction, but the basis for selecting input vectors of the model was not specified. Others have integrated the artificial neural network model with the GARCH model to study the index of the Turkish stock market over the past two decades. The results showed that the ann-apgarh model possessed excellent prediction capacity, but still couldn’t handle large amounts of scatter data [16].

During the same period, Chinese researchers have also conducted some research on neural networks. However, since the stock market involved much abnormal and nonlinear data, and great fluctuation trend, most forecasting models still fail to predict accurately. Nevertheless, neural networks have the advantages of distributed processing and self-learning, self-monitoring, and correcting errors, which are feasible and desirable for predicting a large amount of complex volatility data such as stock prices. Therefore, the present study mainly explores how to choose and how to pre-process samples, the choice of neural network topology (including the number of neurons, the number of hidden layers, input and output functions and attributes, etc.) as well as the self-learning ability of the network. Besides, the optimal prediction period of neural networks is also analyzed [17].

The advantages of the neural network include the generalization ability, fault tolerance and distribution, and associative memory and high parallelism. In terms of stock market forecasting, the neural network can judge the future trend of the prices and achieve a certain precision. Meanwhile, the ability of the neural network to establish automation allows many internal processes to be completed automatically. However, its own automation makes its internal change process a black box and impedes the analysis of its internal relationships, which makes it difficult to analyze the impact process and scale of internal factors. In addition, the prediction quality of the neural network depends on the sample used and its own parameters; and different training samples and training methods will change the prediction results. Nevertheless, this study only explores the effect of BP neural network predicting the CSI index in the short term, which is not affected by these shortcomings.

This paper uses the artificial neural network to make short-term predictions on the closing price of the CSI 300. There are about 200 types of artificial neural networks, among which BP neural network is the most widely used. Therefore, BP neural network is selected to make short-term prediction of the closing price of the CSI 300.

This paper takes the time series of the CSI 300 as the research object, and proposes a simple and feasible prediction model to make short-term predictions of the CSI 300. Through the simulation and analysis of the previous data, this study predicts the price trend during 60 days after March 6th, 2018. The prediction results and the actual data are compared to analyze the prediction effect of BP neural network on the index. In addition, by grouping the 60 daily data obtained according to different time
periods of different length, and then comparing the data in different groups with the actual data, the author calculates the prediction accuracy of BP neural network during different time periods, and explores the optimal prediction time period of BP neural network.

3. Research Method

The error back propagation algorithm, namely BP neural network (back propagation neural network), was first proposed by Professor Rumelhart and Professor McCelland in *Parallel Distributed Processing* in 1986, which updates the coefficients of each layer of the neural network by inversely iterating according to the deviation between the network output value and the actual value. Since the BP neural network algorithm has a very powerful mapping ability, it can approach almost all continuous functions. So far BP neural network has still been a research focus in studies related to neural networks. In 2006, Professor Hinton of the University of Toronto first proposed the concept of deep learning. He used an unsupervised learning strategy called layer-by-layer training to extract more abstract and representative features from raw data and effectively train a neural network called deep belief network. Later, Professor Hinton and other scholars proposed the Dropout method for solving the overfitting of neural networks, and proved that layer-by-layer training could effectively improve the generalization ability of deep networks [18]. In 2014, Shinsuke Kimura, Kunikazu Kobayashi, and Masanao Obayashia used a restricted Boltzmann machine to construct a time series prediction model for deep belief networks [19]. In 2016, Matthew Dixon, Diego Klabjan, and Jin Hoon Bang proposed a deep neural network for predicting the medical manufacturing market based on deep learning [20]. In the following, this paper first briefly introduces the BP neural network and then uses it to make short-term predictions of the CSI 300.

3.1 The Theoretical Model of BP Neural Network

The BP (back propagation) neural network was first introduced in 1986 and is currently one of the most widely applied in neural network models. The BP neural network is a typical multi-layer neural network in which each neuron between layers is directly connected and has a weighted connection. Generally, a BP neural network has three or more layers of neurons, including an input layer, a hidden layer, and an output layer; and there is no connection between neurons of the same layer. Within a BP neural network model, information transmitted by the upper layer of neurons is integrated and then output to the next layer; after the errors between the network output and the actual output sample are compared, the output data is returned to the input layer via each hidden layer; and the weight of each connection is corrected one by one during the return process. This algorithm for repeatedly modifying the weight is thus called the “back propagation algorithm”, whose network structure is shown as follows.

![Figure1. The structure of BP neural network](image-url)
The BP neural network algorithm is implemented as follows:

The input vector is:

\[ X = (x_1, x_2, ..., x_i, ..., x_n)^T \]

The output vector of the hidden layer is:

\[ Y = (y_1, y_2, ..., y_j, ..., y_m)^T \]

The output vector of the output layer is:

\[ O = (o_1, o_2, ..., o_k, ..., o_l)^T \]

The expected output vector is:

\[ d = (d_1, d_2, ..., d_k, ..., d_l)^T \]

The weight matrix between the input layer and the hidden layer can be expressed as:

\[ V = \left( V_{11}, V_{12}, ..., V_{1j}, ..., V_{jn} \right) \]

where, the column vector \( V_j \) is the weight vector corresponding to the \( N_j \) neuron of the hidden layer.

The weight matrix between the hidden layer and the output layer can be expressed as:

\[ W = \left( W_{11}, W_{12}, ..., W_{jk}, ..., W_{kn} \right) \]

where, the column vector \( W_k \) is the weight vector corresponding to the \( N_k \) neuron of the output layer.

As for the output layer, there are:

\[ O_k = f(net_k) \quad k = 1, 2, ..., l \tag{1-1} \]

\[ net_k = \sum_{j=0}^{m} w_{jk} y_j \quad k = 1, 2, ..., l \tag{1-2} \]

As for the hidden layer, there are:

\[ y_j = f(net_j) \quad j = 1, 2, ..., m \tag{1-3} \]

\[ net_j = \sum_{i=0}^{n} v_{ij} x_i \quad j = 1, 2, ..., m \tag{1-4} \]

Assuming that the network output is not equal to the expected output; and there is an output error \( E \), which is defined as:

\[ E = \frac{1}{2} \sum_{k=1}^{l} (d_k - o_k)^2 \tag{1-5} \]

The above equation is expanded in the output layer as:

\[ E = \frac{1}{2} \sum_{k=1}^{l} \left( d_k - f \left( \sum_{j=0}^{m} w_{jk} f \left( \sum_{i=0}^{n} v_{ij} x_i \right) \right) \right)^2 \tag{1-6} \]

The error signals for the output layer and the hidden layer is defined respectively as:

\[ \delta^o_k = -\frac{\partial E}{\partial net_k} \tag{1-7} \]

\[ \delta^y_j = -\frac{\partial E}{\partial net_j} \tag{1-8} \]

An equation can be obtained by combining (1-2) and (1-7):

\[ \Delta o_{ij} = \eta \delta^o_k y_j \tag{1-9} \]

An equation can be obtained by combining (1-4) and (1-8):

\[ \Delta y_{ij} = \eta \delta^y_j x_i \tag{1-10} \]

Weight adjustment formula for each layer can be obtained by combining the above equations.
Output layer has:
\[ \Delta o_{j}^{h+1} = \eta(d_k - o_k)(1-o_k)y_{j}^{h} \quad j = 0, 1, 2, ..., m_h \quad k = 1, 2, ..., l \quad (1-11) \]

Hidden layer \( h \) has:
\[ \Delta o_{i}^{h} = \eta \left( \sum_{j=1}^{m_{h-1}} \delta_{j} \alpha_{i j}^{h+1} \right) y_{j}^{h} (1-y_{j}^{h}) y_{j}^{h-1} \quad i = 0, 1, 2, ..., m_{h-1} \quad j = 1, 2, ..., m_h \quad (1-12) \]

[21]
The training process of the entire BP neural network is as follows:
Step1. The neural network is initialized, including the setting of weights and thresholds.
Step2. Training samples are input.
Step3. Output of each layer is calculated.
Step4. Training error \( E \) is calculated.
Step5. Weights and thresholds are corrected.
Step 3, step 4 and step 5 compose a training cycle.
An accuracy \( \varepsilon \) is set for the experiment; and the training ends when the error \( E \) is less than the accuracy \( \varepsilon \). Conversely, if the accuracy does not meet the requirements, the training process will go back to step 2 and continue with a new training cycle.
A flowchart of the BP neural network is shown in figure 2.

\[ fi (net_{j}, \theta_{j}) = \frac{1}{1 + e^{-net_{j} - \theta_{j}}} \]
is used in the output layer and the hidden layer.
The specific steps are as follows:
Step1. Basic data for the experiment is extracted.
Step2. Data obtained in step1 is divided into training group (3,020), test group (60) and validation group (60).
Step3. The BP neural network is initialized, with the training times set as 1000, the learning rate as 0.1, and the target minimum error as 0.00004.
Step4. The experimental data is made as the input of the BP neural network to train the neural network.
Step5. The indicators of the training group, the test group and the validation group are obtained.
Step6. The prediction results of BP neural network are evaluated based on the analysis of the indicators.
Step7. Trading data during the 60 days after March 6th, 2018 is predicted, and then divided into 5-day, 10-day, 15-day, 20-day, 25-day, 30-day, 35-day, 40-day, 45-day, 50-day, 55-day, and 60-day groups. The impact of the length of time period on prediction accuracy is then analyzed.

4. Empirical Analysis

4.1 Data Source and Descriptive Statistics
This paper selects the daily closing price of the CSI 300 from April 8th, 2005 to March 6th, 2018 as the research object, whose descriptive statistics are shown in Table 1 below.

| Variable  | Symbol | Sample | std    | max    | min    | mean    |
|-----------|--------|--------|--------|--------|--------|---------|
| CSI index | HS300index | 3139 | 1010.548 | 5877.200 | 818.030 | 2861.831 |

4.2 Predicted Results
The short-term prediction of the CSI 300 by the BP neural network is evaluated. The simulated goodness of fit is shown in Table 2 and the absolute and relative errors are shown in Table 3.

| Goodness of fit | Goodness of fit |
|-----------------|-----------------|
| Training goodness of fit | 0.99847 |
| Correction goodness of fit | 0.99799 |
| Test goodness of fit | 0.99849 |
| Overall goodness of fit | 0.99840 |
Figure 3. Trained Goodness of fit

Table 3. Prediction effect of the BP neural network

| Error type         | Mean absolute error | Mean relative error |
|--------------------|---------------------|--------------------|
| Training: R=0.99847| 0.0124              |                    |
| Validation: R=0.99799|                    |                    |
| Test: R=0.99849    | 36.6387             | 0.0124             |
| All: R=0.9984      |                     |                    |

The output of the BP neural network test set sample is shown in Figure 4; the error is shown in Figure 5; and the percentage of error is shown in the Figure 6.
Table 2 shows that the training goodness of fit is 0.99847, the correction goodness of fit is 0.99799, the test goodness of fit is 0.99849, and the overall goodness of fit is 0.9984, which indicate that the BP neural network possesses good fitting effect. Table 3 shows that the mean absolute error is 36.6387 and the mean relative error is 1.24%, indicating that the BP neural network has no over-fitting in the short-term prediction and has good prediction effect on the whole. The results of the short-term forecast are shown in Table 4.
Table 4. Results of the short-term prediction by the BP neural network

| Prediction period | Predicted value | Prediction period | Predicted value | Prediction period | Predicted value | Prediction period | Predicted value |
|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|
| 1                 | 4049.313        | 16                | 3890.731        | 31                | 3831.993        | 46                | 3804.581        |
| 2                 | 4032.93         | 17                | 3884.977        | 32                | 3829.524        | 47                | 3803.306        |
| 3                 | 4017.488        | 18                | 3879.583        | 33                | 3827.171        | 48                | 3802.081        |
| 4                 | 4003.013        | 19                | 3874.52         | 34                | 3824.928        | 49                | 3800.904        |
| 5                 | 3989.496        | 20                | 3869.761        | 35                | 3822.788        | 50                | 3799.771        |
| 6                 | 3976.909        | 21                | 3865.282        | 36                | 3820.746        | 51                | 3798.682        |
| 7                 | 3965.208        | 22                | 3861.062        | 37                | 3818.794        | 52                | 3797.634        |
| 8                 | 3954.339        | 23                | 3857.081        | 38                | 3816.929        | 53                | 3796.624        |
| 9                 | 3944.245        | 24                | 3853.321        | 39                | 3815.144        | 54                | 3795.653        |
| 10                | 3934.869        | 25                | 3849.766        | 40                | 3813.436        | 55                | 3794.716        |
| 11                | 3926.153        | 26                | 3846.401        | 41                | 3811.801        | 56                | 3793.814        |
| 12                | 3918.045        | 27                | 3843.212        | 42                | 3810.234        | 57                | 3792.945        |
| 13                | 3910.493        | 28                | 3840.188        | 43                | 3808.732        | 58                | 3792.106        |
| 14                | 3903.452        | 29                | 3837.316        | 44                | 3807.291        | 59                | 3791.298        |
| 15                | 3896.877        | 30                | 3834.588        | 45                | 3805.908        | 60                | 3790.517        |

The true and predicted values of the CSI 300 from March 6, 2018 to June 4, 2018 are described in Figure 7 below, which shows that: the CSI 300 would follow a downward trend as a whole during the 60 days after March 6th, 2018; the CSI 300 would undergo small fluctuation frequency during the 60 days after March 6th, 2018; and the CSI 300 would decrease from 4066.57 to 3807.58 during the 60 days after March 6th, 2018, with a decrease of 6.79% and small price fluctuations.
prediction values. The results are shown in Figures 8, 9, 10, and 11, and the values are shown in Table 5.

Table 5. Comparison of predicted results of different prediction periods of BP neural network with real data

| Prediction period | Mean relative error | Mean absolute error | Precision of rise and fall of the same period | Numerical precision |
|-------------------|---------------------|---------------------|-----------------------------------------------|---------------------|
| 5                 | 0.0183              | 75.0252             | 0.4000                                        | 0.2000              |
| 10                | 0.0239              | 97.7436             | 0.4000                                        | 0.1000              |
| 15                | 0.0206              | 84.0097             | 0.5333                                        | 0.2667              |
| 20                | 0.0167              | 67.7914             | 0.5500                                        | 0.4000              |
| 25                | 0.0156              | 63.1346             | 0.5600                                        | 0.4000              |
| 30                | 0.0152              | 60.7596             | 0.5667                                        | 0.4333              |
| 35                | 0.0147              | 58.4147             | 0.5714                                        | 0.4286              |
| 40                | 0.0142              | 56.2188             | 0.5250                                        | 0.4250              |
| 45                | 0.0148              | 58.4505             | 0.5111                                        | 0.3778              |
| 50                | 0.0159              | 62.4984             | 0.5000                                        | 0.3400              |
| 55                | 0.0156              | 61.4433             | 0.5273                                        | 0.3455              |
| 60                | 0.0149              | 58.4533             | 0.5333                                        | 0.3833              |

Figure 8. Mean absolute errors of BP neural network under different groups
Figure 9. Numerical accuracy of BP neural network under different groups (accuracy 0.01)

Figure 10. Mean relative error of BP neural network under different groups

Figure 11. Precision of rise and fall of BP neural network under different groups
It can be seen from Table 5 and Figures 8, 9, 10, and 11 that the mean relative errors and mean absolute errors of the groups of 30-day, 35-day, and 40-day are smaller than those of the other groups. Besides, the groups of 30-day, 35-day, and 40-day demonstrate high numerical accuracy and accuracy of rise and fall prediction, with the numerical accuracy being above 42% and the accuracy of the rise and fall prediction being more than 55%.

5. Conclusion
This paper uses the BP neural network to make a short-term forecast of the daily closing price of the CSI 300 from March 7th, 2018 to June 20th, 2018. According to the results of goodness of fit, absolute errors and relative errors, the BP neural network model possesses good prediction effect. The forecast results show that from March 7th, 2018, the daily closing price of the CSI 300 in the next 60 days would: (1) follow a downward trend on the whole; (2) undergo small fluctuation frequency; and (3) undergo small price fluctuations.

By dividing the prediction results of the 60 days and comparing them with the actual data, the author finds that: (1) the prediction of a time period shorter than 20 days or longer than 50 days incurs larger errors; (2) the prediction of a time period of 30 to 40 days is more accurate; and (3) for prediction of a time period of more than 50 days, prediction errors will increase sharply, and thus cannot be predicted by the neural networks.

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