Team Control Number

20201008820

Problem Chosen

B

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ShuWei Cup

Summary

In recent years, stocks have become more and more important tools for people to invest, but the changes in stock prices are affected by many factors. The stock price on the securities market is affected by external international politics, financial policy macro factors, corporate operating conditions, fluctuations between sectors and other micro factors. So how to scientifically predict the changes of stock prices has important theoretical and practical significance. Therefore, accurate prediction of stock market prices has become a research hotspot now.

For question one, after our preliminary analysis of the data, we found that the direct use of the source data cannot perform long-term trend analysis. Therefore, we have established a Moving Average Model to eliminate the influence of periodic changes and random fluctuations, thereby showing the development direction and trend of events.

For question two, we need to find a mathematical model to deal with this multivariate nonlinear problem. We built a BP neural network model, and imported 6 variables from the data into the algorithm for model training, to find the best *MSE* result to make the most accurate predictions for the last 20 days through the trained model.

As for question three, we establish a stock reversal judgment model[5] based on the results of question two to determine whether the stock will rise or fall at a certain point. We handpicked 40-50 subjective "turning points" from the result of question two, then applied them to the model in question three, therefore it will tell us whether there is a reversal model in the second question.

Key word: Stock predictions, Moving Average, BP neural network, MSE

Content

1. Introduction

1.1 Background

The change of stock price of any companies can directly reflect the operation status of them and the recognition degree of the market. The modeling and forecasting of stock price are always a difficult problem. The most important factor is that the stock price has both trend and random factors. Therefore, the stock market is a very typical nonlinear complex system. In the aspect of solving nonlinear complex system modeling, practice has proved that chaos theory is an effective theory, and has achieved certain theoretical and application effects in power, communication and other fields. As the stock market is also a nonlinear and complex system, can we use the idea and theory of chaos theory to establish the stock price model?

1.2 Work

Use the mathematical modeling method to solve the following problems with the transaction data of three stocks provided:

① Analyze the daily, weekly and monthly trend of the three stocks, and qualitatively or quantitatively analyze the trend of the stocks (including the test of chaotic characteristics), and give the relevant analysis results (Note: the weekly and monthly data of stock prices can be determined by daily data).

② According to the trend of different stock prices, we try to establish the mathematical model of stock price trend and randomness, and use the data of the last 20 days to evaluate the prediction results of the model.

③ There is a reverse phenomenon in the trend of stock price, that is, if it goes up too much, it will fall, and if it falls too much, it will rise, showing a certain cyclical change. Please use the research results of question two to establish the stock price reversal judgment model and test it with data.

2. Problem Analysis

2.1 Data Analysis

As the given data shown to be stock prices, to judge whether the data is reasonable, we imported the given data into SPSS to draw line charts of close price, but we can find that the price fluctuations are phenomenal. Thus, we adapted the Moving Averages (MA)[1] from statistics. After importing and applying MA (with previous n-day data which is set to 10) to three given stock datasets, we now have three MA figures.

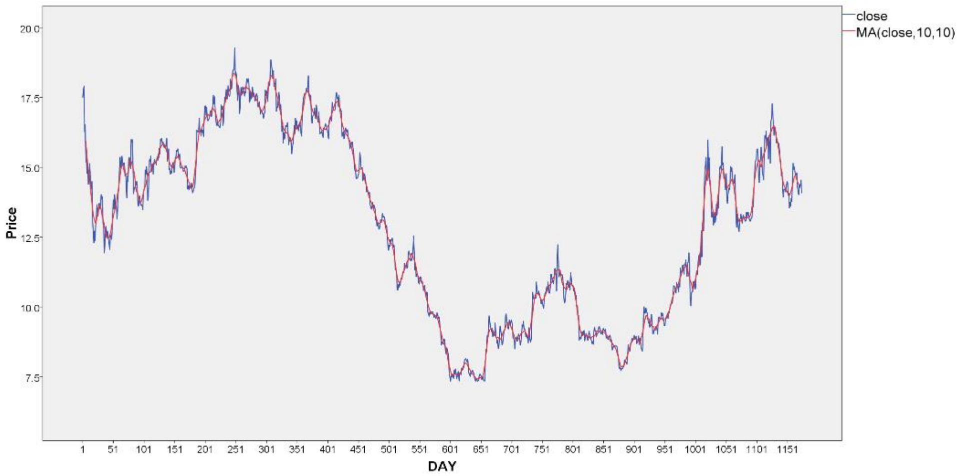

Figure 1 000400.SZ MA10

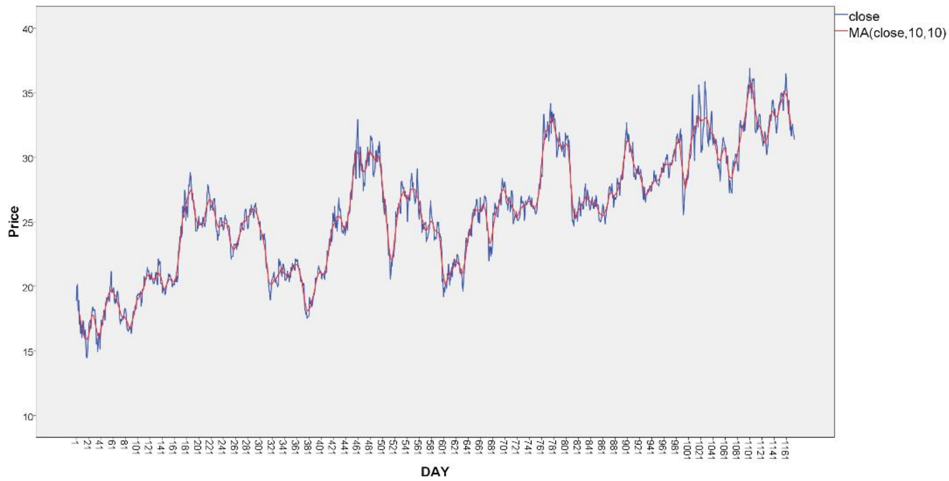

Figure 2 002281.SZ MA10

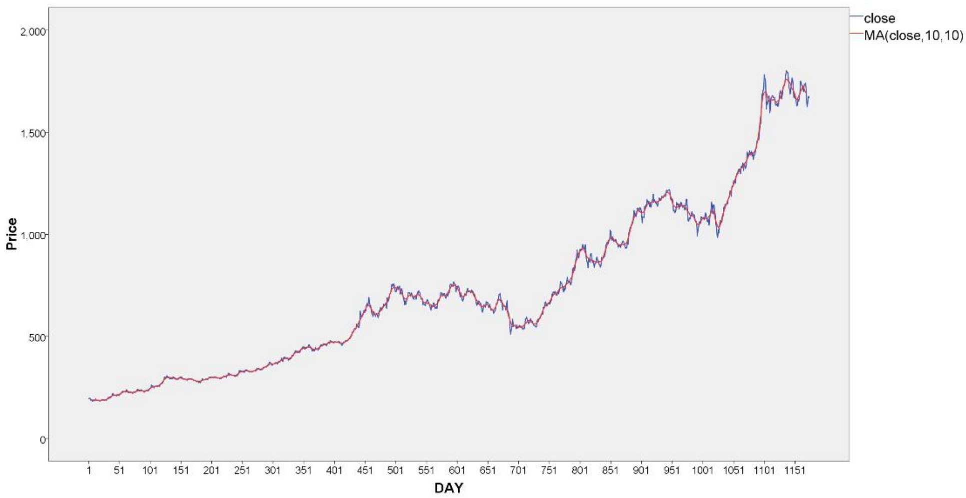

Figure 3 600519.SH MA10

After smooth out short-term fluctuations and highlight longer-term trends or cycles, we can clearly see the trend of each specific stock, which is easier for further analysis.

2.2 Analysis of question one

The first question needs us to analyze the daily, weekly and monthly trend of the three stocks, and qualitatively or quantitatively analyze the trend of the stocks including chaotic characteristics test.

And we adopted a qualitative method to analyze stock market trends.

First, it is obvious that this question is a typical time series problem, so it is possible for us to build a time series model based on Moving Average theory. Thus, we imported the "close price" data in the set, we applied the Moving Average to three sets of data to get the daily interval trend, weekly interval trend, and monthly interval trend. To further simplify calculations, we took daily interval as 1, weekly interval as 5, monthly interval as 30[1].

Then, from the three MA lines, we can see the trend of the stocks according to the time series.

Therefore, we can use the power spectrum to analyze the time series.

2.3 Analysis of question two

The second question needs us to create a mathematical model using given data, and then use the data of last 20 days to evaluate the prediction results of the model. Stock trading data prediction is a time series forecast. In this extremely complex system of the stock market, it has factors such as turbulence, nonlinearity, and high noise. So, we can use BP neural network to predict the price. BP network can approximate arbitrarily complex continuous function relations, and these abilities are not available in traditional methods[2].

2.4 Analysis of question three

We need to establish a stock reversal judgment model for the question two, to determine that if there is a reverse phenomenon in the trend of stock price. For this question, we need to know the concept of "if it goes up too much, it will fall, and if it falls too much, it will rise". Thus, we need to define these two specific patterns, a "turning point", and an "indication sequence".[5] Then we need to find the judgment condition for them.

3. Symbol and Assumptions

3.1 Symbol Description

Notations	Definitions
$\boldsymbol{n}$	Number of moving average periods
$\boldsymbol{F_t}$	Forecast of next value
$\boldsymbol{A_{tn}}$	Actual value of period n

$\boldsymbol{x_n}$	Neural network input data *x*
$\boldsymbol{w_{sn}^{(1)}}$	Neural network hidden layer one
$\boldsymbol{w_{ms}^{(2)}}$	Neural network hidden layer two
$\boldsymbol{y_m}$	Neural network output data *y*
$\boldsymbol{MSE}$	Mean-Square Error
N_s	Total number of samples
O_t	Neural network prediction output value
T_t	True value of data
O_{RP}	Output of Reversal Point prediction
M_{RP}	Manually marked Reversal Point
$\boldsymbol{t}$	The number *t* Sample
$\boldsymbol{a}$	Days count
$\boldsymbol{b}$	Days count
$\boldsymbol{a_{rp}}$	Number of output reversal points
$\boldsymbol{b_{mk}}$	Manually marked reversal points
$t3$	Time
$\boldsymbol{A}$	Given positive value
$\boldsymbol{B}$	Given positive value
$close_{t3-a}$	Close price at the certain *Time*
$close_{t3+b}$	
$close_{t3}$	
SRC_x	Turning point date sets.

3.2 Fundamental Assumptions

(1) We assume that the data it provides are authentic.
(2) We assume that the data can objectively reflect the stock price without any intervenes.
(3) We assume that COVID-19 pandemic won't cause sudden changes in stock prices.

4. Models and Results

4.1.1 Moving Average Model based on time series.

A moving average model is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. The threshold between short-term and long-term depends on the application, and the parameters of the moving average will be set accordingly. Mathematically, Moving Average can be regarded as a kind of convolution.

The formula of a simple moving average can be described as follows:

$$\boldsymbol{F_t = \frac{A_{t1} + A_{t2} + A_{t3} + \cdots + A_{tn}}{n}}$$

Formula 1 Simple Moving Average

For the question one, we just need to set the Moving Average period ***n*** as 1 for daily, 5 for weekly, 10 for monthly.

After importing the three given data sets into SPSS, we established three MA lines based on the above three values, and now there are three figures corresponding to these three lines.

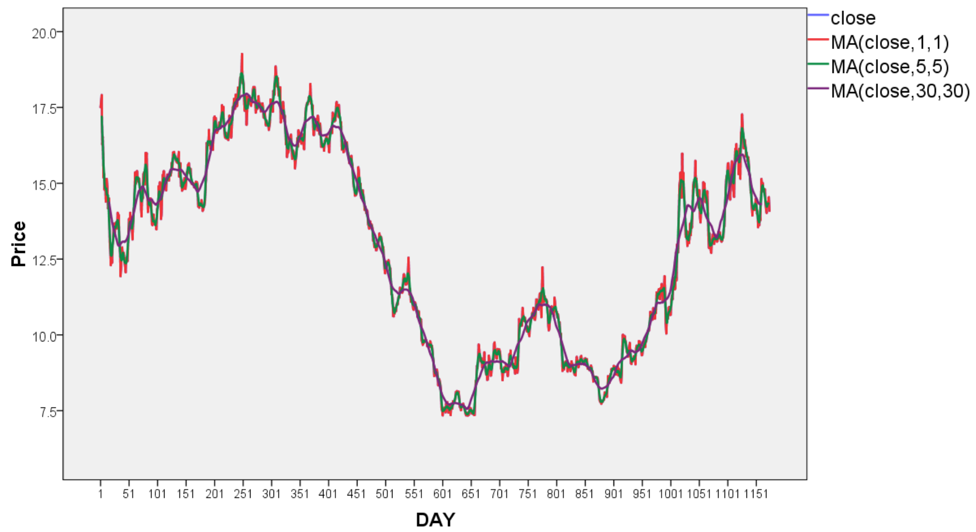

Figure 4 MA1&MA5&MA30 of 000400.SZ

According to the MA30 line in Figure 4, we can clearly see that between day 1 – 250, the close price is on a positive trend. And it has a slight negative trend between day 290 – 340, after day 400, it keeps a negative trend for nearly 250days. After that it had a price fluctuates for about 5yuan between day 650 – 870, and for the rest of days, the price generally maintained a positive trend.

And as for qualitative analysis, we learned that the company's main business is manufacture power grid automatic distribution equipment. And it is a leading company in China's power equipment industry, it also has successively provided many equipment for the "West-to-East Power Transmission", "West-to-East Gas Transmission" projects, as well as hydropower, nuclear power, railway construction and other national large-scale engineering project. Therefore, this company's stock price will not rise or fall significantly, and generally remains stable.

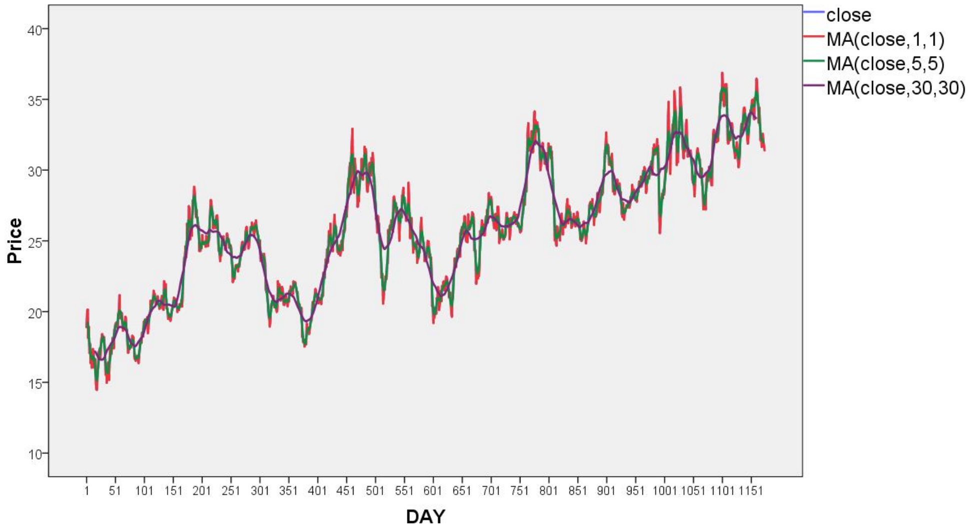

Figure 5 MA1&MA5&MA30 of 002281.SZ

In Figure 5, we can see that the price shows a phenomenon of repeated fluctuations, but overall the price is still on a positive trend.

Qualitatively speaking, the reason for the overall increase in the company's stock price is that it is the only high-tech company in China capable of conducting comprehensive research and development on optical fiber amplifiers and subsystems, optical passive components and planar integrated optical waveguide devices. It cooperates with many well-known telecommunications companies around the world. And with the rapid development of China's communication technology in recent years, like 5G technology, the rise in stock prices is also reasonable.

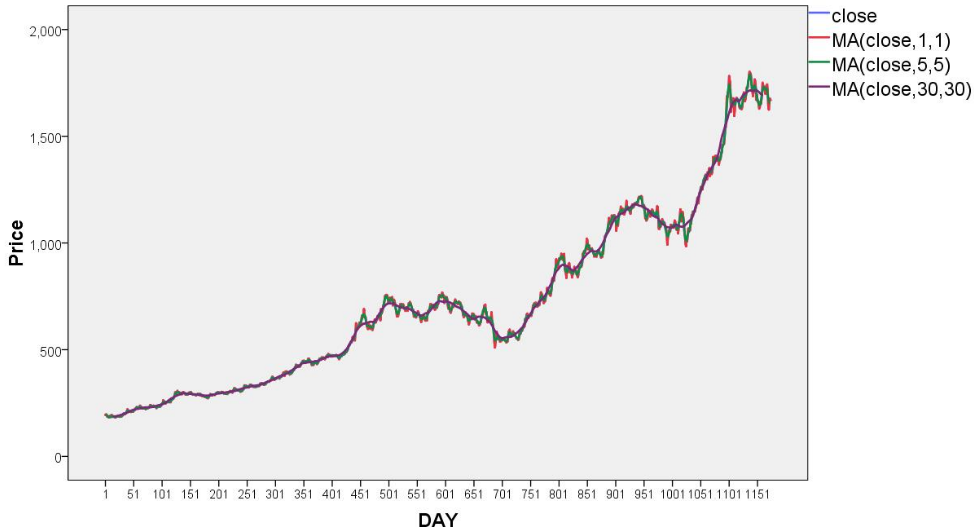

Figure 6 MA1&MA5&MA30 of 600519.SH

And for Figure 6, the positive trend of price is obvious.

By looking at the three lines, we can see that higher the period n is set, the smoother the line is. This means that in daily and weekly price analysis, it is impossible to intuitively understand the positive and negative trends of the stock. Therefore, to see the trends intuitively, the period value n should be set larger, so that the resulting Moving Average line will not be easily affected by periodic changes and random fluctuations.

We got a conclusion after qualitative analysis. There are two main reasons why the stock price is keep rising.

(1) Strong brand influence

Kweichow Moutai has a long history and profound cultural connotations. It is famous at home and abroad for its excellent quality. And today's Moutai has been considered as a super luxury brand.

(2) Unique craftsmanship

Moutai is the only natural fermentation product among the world-famous wines. Its uniqueness is mainly reflected in the 5-year aging process, using high-quality materials, and going through a very complicated brewing process, which competitors are impossible to copy and imitate, created a non-replicability of Moutai.

4.1.2 Chaotic Characteristics analysis

Chaos theory is the analysis of irregular and unpredictable phenomena and their processes. A chaotic process is a deterministic process. As the question mentioned, multiple practices have proved that chaos theory is an effective theory, and has achieved certain theoretical and application effects in power, communication and other fields.

Research shows that the power spectrum can clearly show whether there is chaos in a certain time series. Chaos is characterized by the appearance of "noise background" and "broad peaks" in the power spectrum, which reflects the chaotic motion has the randomness of a certain system. [4]

Therefore, after importing the 000400.SZ data into MATLAB, we now have a power spectrum figure. We can see that there are obvious "noise background" and "broad peaks" in the power spectrum, which proves that the changes in stock prices have chaotic characteristics.

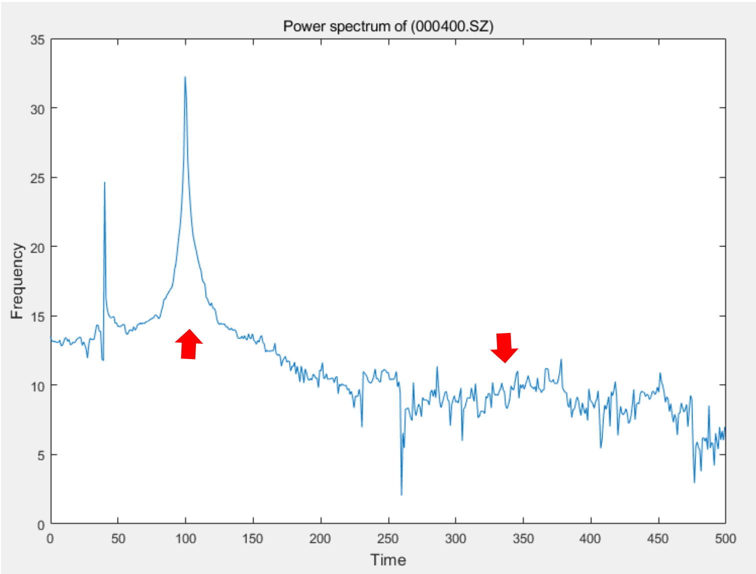

Figure 7 Power Spectrum of 000400.SZ

4.2 BP Neural Network Model

4.2.1 Establish BP Neural Network Model

As for question two, we introduced a BP neural network[2], the neural network consists of 3 neurons: the input layer, the hidden layer, and the output layer.

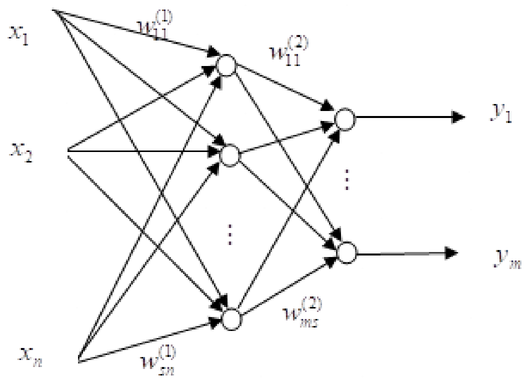

Figure 8 A BP neural network

The left is the input layer, the input layer is composed of a large amount of data, the middle two layers are hidden layers, and the right is the output layer.

In the input and hidden layer, the transfer function generally uses the activation function, and the same for hidden and output layer.

In theory, a multilayer neural network can fit any function.

Thus, we established a model based on the stock trend prediction model of BP neural network. The algorithm flow chart of BP neural network in stock trend prediction is as follows:

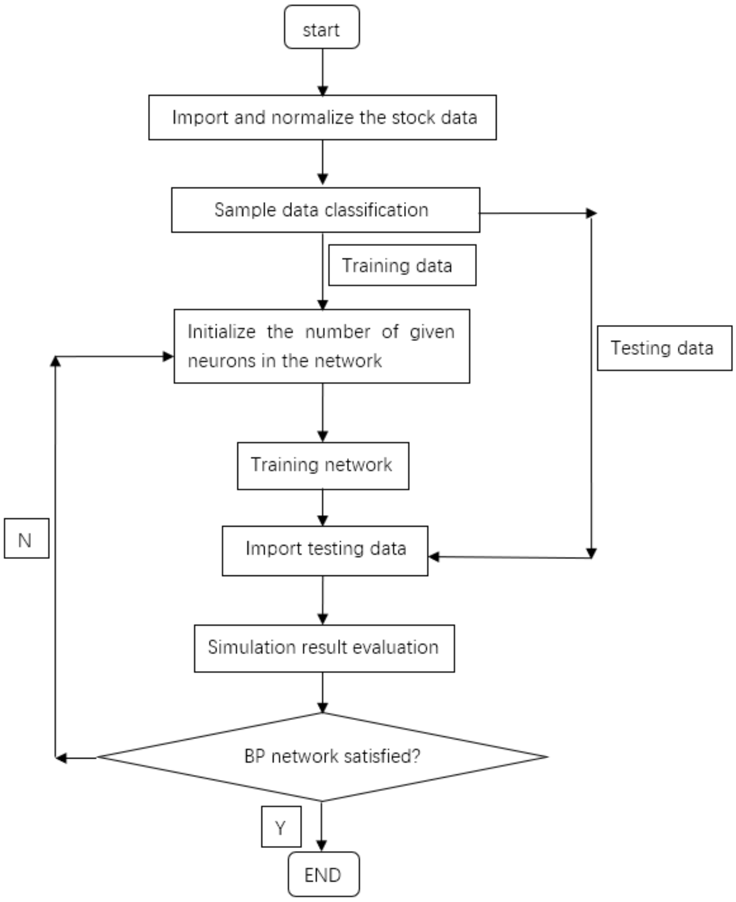

Figure 9 Algorithm flow chart of BP neural network in stock trend prediction

For the input variables, this paper uses the opening price, closing price, highest price, lowest price, trading volume, and turnover rate of the three-stock data provided in the attachment as input variables. Considering that the closing price of the stock price is the most important, and it is the only variable that measures the daily stock prices' rise and fall, so we only choose the closing price as the output.

To allow the BP neural network to better predict the real stock trend and closing price, the following optimization methods are used while training the neural network:

(1) Since the hidden layer is an important parameter that affects the prediction of the BP neural network, and the selection of the parameter directly affects the error rate of the BP network prediction. This paper has experimented with the impact of different hidden layers on the network performance, and set hidden layers from 5 to 15 to obtain 10 BP neural networks with different structures, and then obtain the Mean-Square Error(MSE) under different BP neural networks.

(2) Data pre-processing and post-processing are also important for effective training of our neural networks. In this paper, the input data is limited to the [-1,1]

interval through a certain linear transformation. The standardized data eliminates the order of magnitude difference between the input quantities. For example, there is a large order of magnitude difference between stock price and trading volume. If it is not standardized, when the neural network calculates the weights and thresholds, the weights and thresholds related to trading volume may become very small.

4.2.2 MSEs in BP neural network

The MSE is the average of the sum of squares of the distances that each data deviates from the true value. The formula of MSR can be described as follows:

$$MSE = \frac{1}{N_s}\sum_{t=1}^{N_s}(O_t - T_t)^2$$

Formula 2 MSE

The N_s, O_t, T_t are the Total number of samples, Neural network prediction output value and the True value of data. In this paper took the last 20 days of transaction data of the three stocks as the true value, the BP neural network prediction data is used as the prediction output value to get MSE results.

Obviously, the smaller the value, the more accurate the prediction is.

To show the prediction effect of the BP neural network more clearly, this paper introduced a prediction accuracy P_BP of the BP network:

$$P\_BP = 1 - \frac{\sum_t |O_t - T_t|}{\sum_t |T_t|}$$

Formula 3 BP network prediction accuracy

The value of P_BP is between 0-1, the closer to 1, the higher the accuracy of the BP network is, the closer to 0, the lower the accuracy of the BP network is.

4.2.3 Training the BP neural network

According to the algorithm, we used the neural network toolbox within MATLAB to set data from day 1 to day 1154 as the training set to train the neural network.

During training, we used 6 variables: open, high, low, close, volume, and turn as the input vector of the network, and the closing price predicted by BP as the output value. Its neural network structure is shown in the figure below:

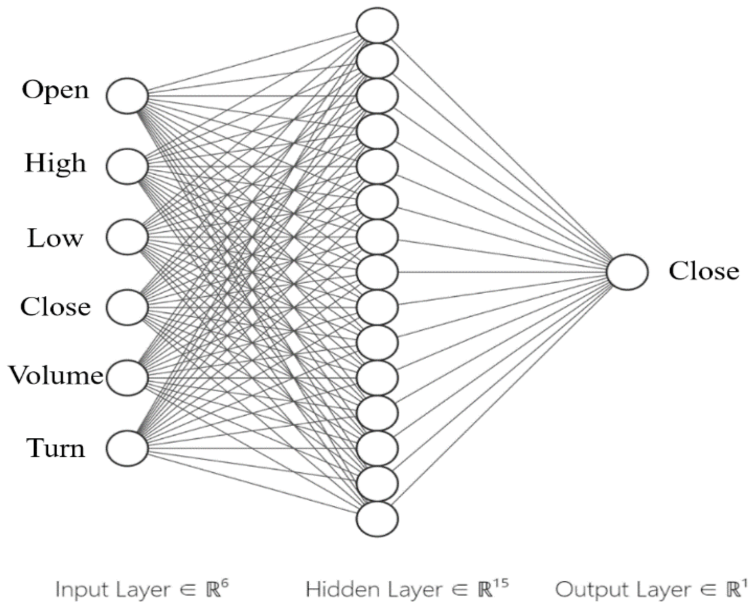

Figure 10 BP neural network structure

After setting hidden layers from 5 to 15 to obtain 10 BP neural networks with different structures, we now have 10 MSE results:

Hidden layers	000400(SZ)	002281(SZ)	600519(SH)
5	1.0791e-04	0.0014	4.5212
6	1.0195e-04	0.0012	0.6403
7	1.0619e-04	0.0074	14.8985
8	1.9262e-04	0.0020	13.9506
9	1.1088e-04	0.0021	10.0021
10	6.7878e-05	0.0061	11.0084
11	1.0279e-04	0.0056	30.2759
12	3.1877e-05	0.0031	2.7188
13	1.4911e-04	0.0042	13.3483
14	2.0274e-04	0.0015	11.5916
15	1.2799e-04	0.0028	13.1531

Table 1 Different MSE results of different hidden layers

Through the data in this table, we can know the optimal number of hidden layers of the BP neural network required to predict the closing price of each stock. For 002281.SZ, the number of layers is 6 and the BP neural network has the best prediction currently. Similarly, we can find that for 600519.SH, the number of layers is 6 and for 000400.SZ, the number of layers is 12.

4.2.4 Predictions of BP neural network

According to the above results, we have obtained the best BP neural network structure for the three stocks with stocks.

Thus, we use the last 20 data as the test set samples and input the trained BP neural network to obtain the predicted values, and then we compare this value with the stock original data set, and comparisons as follows:

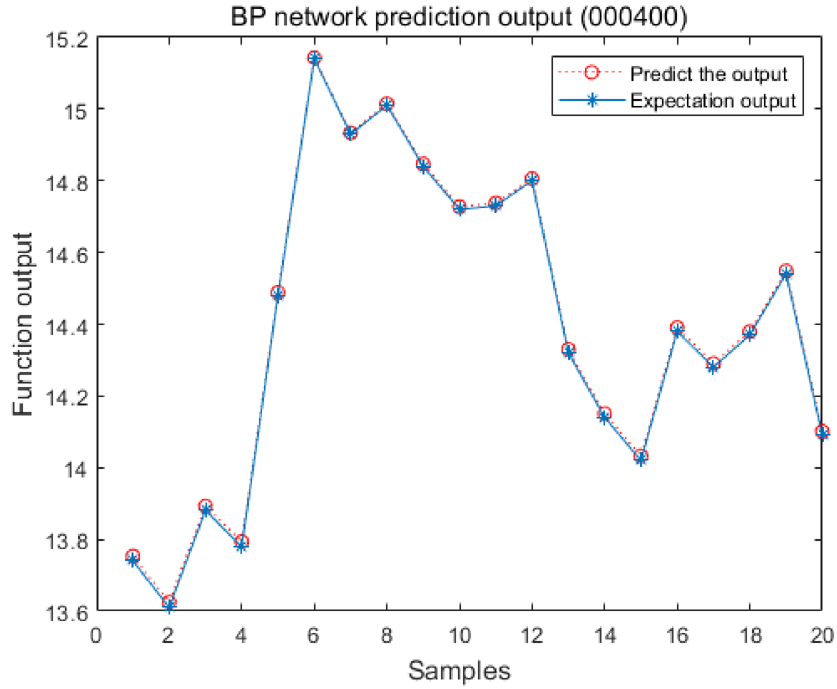

Figure 11 BP network prediction output(000400.SZ)

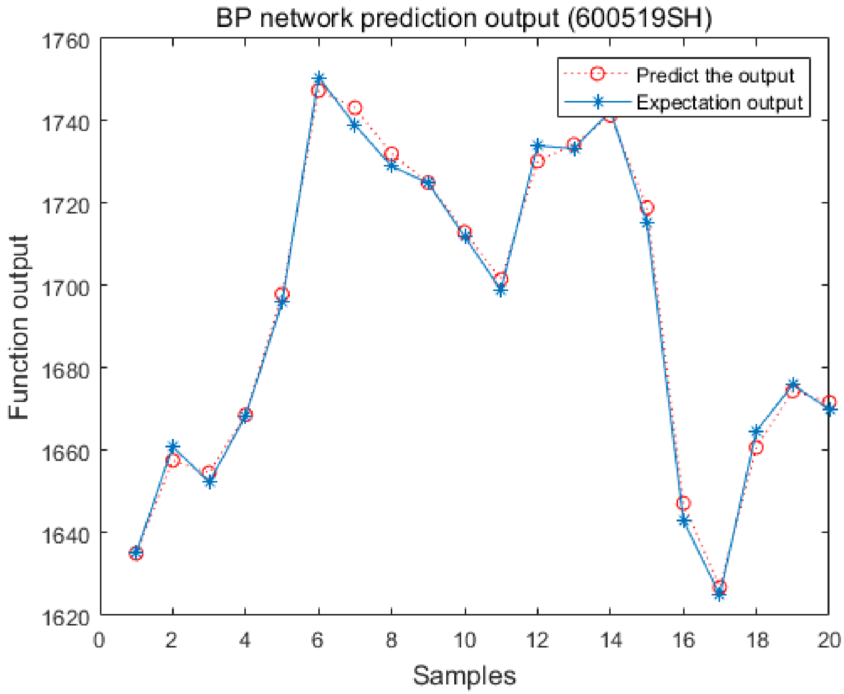

Figure 12 BP network prediction output(600519.SH)

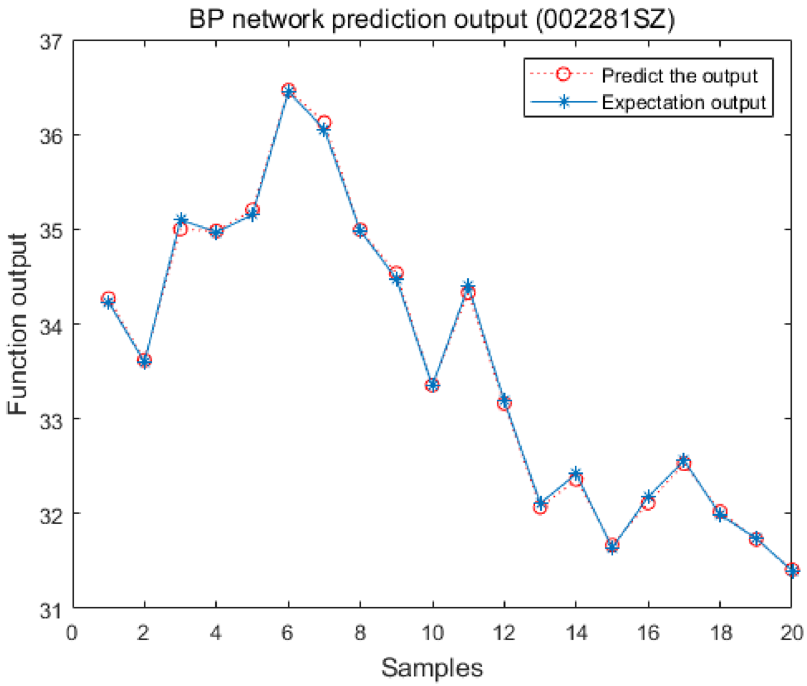

Figure 13 BP network prediction output(002281.SZ)

From the comparison of Figure 10 to Figure 12, we can see that the predicted value of the BP neural network is very close to the true value, indicating that our model is fitting very well. To show the accuracy of the BP model in this article more clearly, we use the accuracy rate P_BP to express it more intuitively:

	000400(SZ)	002281(SZ)	600519(SH)
P_BP	96.11%	95.85%	97.90%

Table 2 BP network prediction accuracy rate

4.3 Stock Price Reverse Model

4.3.1 Definitions of the model

(1) Continuous rise and continuous fall: Rising or falling for a consecutive days does not require that the daily K-line for a days are both positive or negative. In fact, this situation is rare in the stock market (especially when a >=5). In most cases, most stocks will undergo minor adjustments on a certain day or a few days, even in a market that has risen or fallen sharply. Therefore, considering the actual situation, we changed the definition of continuous rise and continuous fall. Within a days, the stock's rise or fall reaches the set value and then it is defined as continuous rise or continuous fall.

(2) Stock price rise reversal point: Decline for b consecutive days and then rise for b consecutive days.

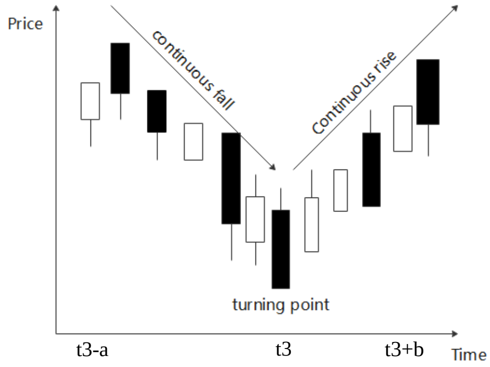

Figure 14 Stock price rise reversal schematic diagram

That is, when the following two conditions are met at the same time:

$$\frac{close_{t3-a} - close_{t3}}{close_{t3-a}} \times 100 \geq A$$

$$\frac{close_{t3+b} - close_{t3}}{close_{t3-a}} \times 100 \geq B$$

Formula 4,5 Price rise reversal point conditions

Then it is considered that the stock price has reversed at time $t3$, and this point is the rise reversal point of the stock price.

(3) Stock price fall reversal point: Rising for a consecutive days and then falling for b consecutive days.

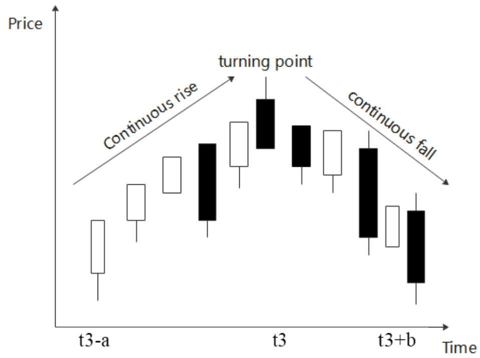

Figure 15 Stock price fall reversal schematic diagram

That is, when the following two conditions are met at the same time:

$$\frac{close_{t3} - close_{t3-a}}{close_{t3-a}} \times 100 \geq A$$

$$\frac{close_{t3} - close_{t3+b}}{close_{t3-a}} \times 100 \geq B$$

Formula 6,7 Price fall reversal point conditions

Then it is considered that the stock price has reversed at time $t3$, and this point is the fall reversal point of the stock price.

4.3.2 Solving the models

The following begins to test the performance of the stock reversal judgment model. The method of testing is to manually mark the rise reversal point of the stock price and the fall reversal point of the stock price of the BP neural network model obtained in question two.

Then, manually set test sets Test1, Test2, Test3 by using the method mentioned above, and then applied the predicted value of the BP neural network model as input data into the stock reversal judgment model to obtain the reversal of the output of the stock reversal judgment model Point the date sets SRC_1, SRC_2, SRC_3, and then compare the test set of the stock with the output reversal point date set.

In the establishment of the accuracy model of the stock price reversal point judgment model, we may encounter the problem of inconsistency between the number of test sets and SRC sets. At this time, if we directly remove the excess data, it will have a greater impact on the accuracy calculation , so in this paper we modified the P_BP in question 2 to get the stock price reversal point accuracy:

$$P\_RP = 1 - \frac{\sum_t |O_{RP} - M_{RP}|}{\sum_t |M_{RP}|} - \frac{|a_{rp} - b_{mk}|}{a_{rp} + b_{mk}} \times 0.3$$

Formula 8 Reversal prediction accuracy

The O_{RP} is the output of reversal point prediction, the M_{RP} is the Manually marked reversal point, $\boldsymbol{a_{rp}}$ and $\boldsymbol{b_{mk}}$ are the Number of output reversal points and Manually marked reversal points. We used the P_RP model subtract an offset to reduce the impact on the accuracy calculation after the redundant data is eliminated. Thus, we made the following comparison charts:

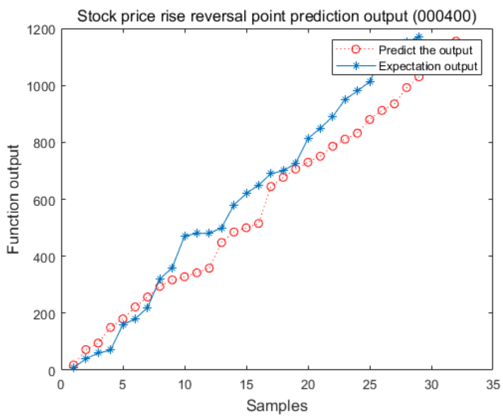

Figure 16 Rise reversal point prediction output

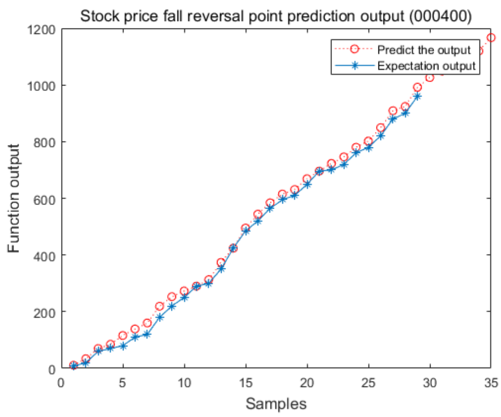

Figure 17 Fall reversal point prediction output

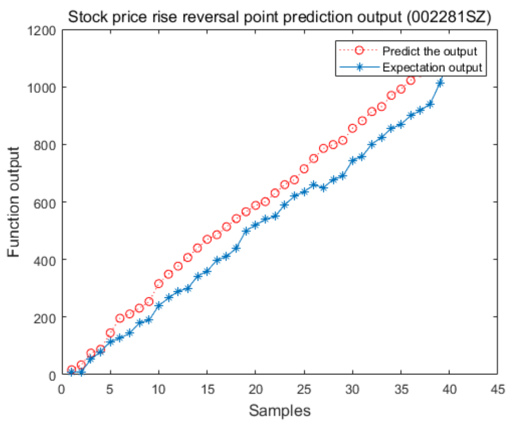

Figure 18 Rise reversal point prediction output

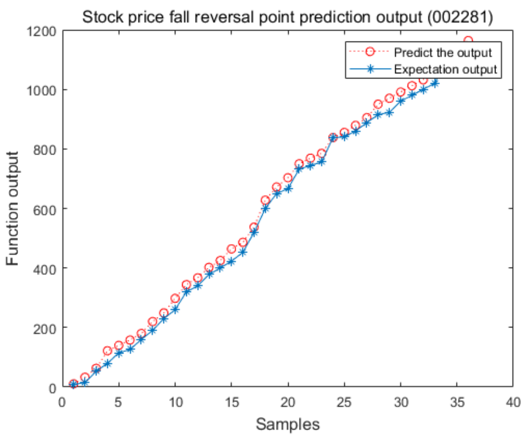

Figure 19 Fall reversal point prediction output

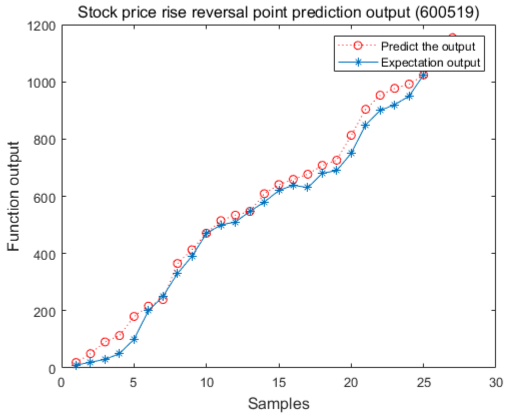

Figure 20 Rise reversal point prediction output

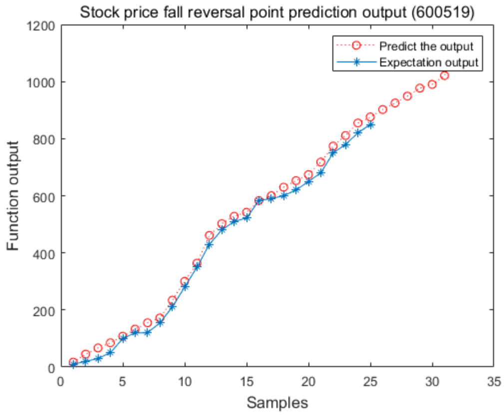

Figure 21 Fall reversal point prediction output

The results are as follows:

000400	Rise	Fall
Number of test sets	40	29
Number of SRC	41	35
Accurate rate	**85.06%**	**95.43%**
002281	Rise	Fall
Number of test sets	40	36
Number of SRC	41	36
Accurate rate	**83.50%**	**95.50%**
600519	Rise	Fall
Number of test sets	25	25
Number of SRC	27	33
Accurate rate	**93.53%**	**94.40%**

Table 3 Reversal prediction results

From the comparison of Figure 16 to Figure 21 and the Table 3, we can see that the model has a good judgment on the reversal points of the three stocks.

5. Sensitivity Analysis

(1) In the moving average model, we can see that when the period value *n* is set to be relatively small, the drawn moving average line is very unsmooth and cannot clearly represent the changing trend in the selected period.

(2) In the BP neural network model, first, we debugged the maximum number of iterations (net.trainParam.epoch) for 500, 1000, 2000, 3000, and at the same time we kept the training goal(net.trainParam.goal) at 0.01%, and found that the result is almost the same, the number of times to reach the training goal is far less than the maximum iterations. Then, we kept the maximum number of iterations at 1000 unchanged, at the same time we adjusted the training target. We found that if the training goal(net.trainParam.goal) is greater than 0.01%, the predictions will have a relatively large deviation. When it is less or equal to 0.001%, the predictions will be relatively accurate. Therefore, we only need to set the training goal(net.trainParam.goal) to 0.01%-0.001%, so that the model can generate a satisfying result.

6. Strengths and Weakness

6.1 Strengths

(1) Moving averages can easily and quickly show the general trend of exchange rate fluctuations.

(2) In BP neural network, its outstanding strengths is that it has a strong nonlinear mapping ability and a flexible network structure. The number of middle layers of the network and the number of neurons in each layer can be set arbitrarily according to the specific situation.

(3) By comparing our BP neural network with traditional Time Series analyze prediction model in the stock market forecast. The traditional regression analysis method is obviously difficult to produce useful information. It is not only difficult to predict the overall volatility trend, but also has big problems in the accuracy of data prediction.

6.2 Weakness

(1) Moving average changes slowly, and it is difficult for investors to easily and conveniently grasp the trough or peak of the exchange rate. As far as the long-term moving average is concerned, this weakness is more conspicuous.

(2) For BP neural network we can clearly see that the learning speed is very

slow, even for a simple problem, it usually takes thousands of learning to converge. And there is no corresponding theoretical guidance for the selection of the number of network layers and the number of neurons.

(3) Although the BP neural network has a wide range of applications, but it is easy to fall into local minima and network paralysis. To fix this, can we increase the momentum term to improve the accuracy and efficiency of the calculation?

7. Conclusion

The stock market is a complex system affected by many factors. As the external manifestation of the stock market, time series data contains a lot of objective rules. Identifying all kinds of information from it for better understanding, mastering and using its rule is undoubtedly of practical significance for financial investment and financing forecasting, decision-making and risk management activities.

This paper mainly focuses on the BP neural network algorithm. We have studied several key factors that affect the prediction effect of the BP network model, the number of layers, the number of nodes, the activation function and the training function. We can know from the approximation theorem, we can find A model approximation that is most suitable for a time series.

If such a most accurate approximation can be found, it’s fitting and forecasting effect will be the best. But, we can only control the influencing factors of the neural network to achieve the accuracy conditions we set in advance.

Even so, we can fully show that its performance in stock market prediction is quite good.

References

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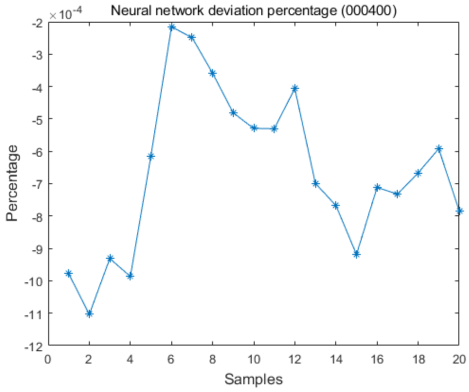
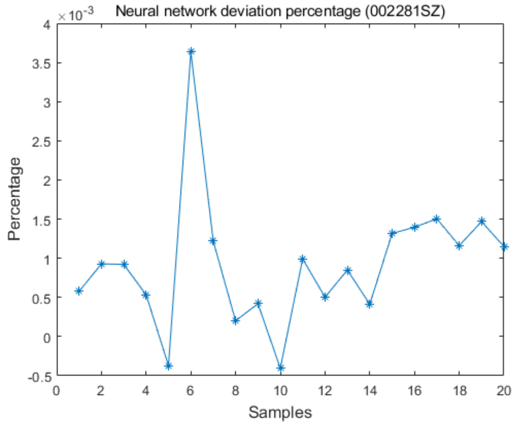
Appendix

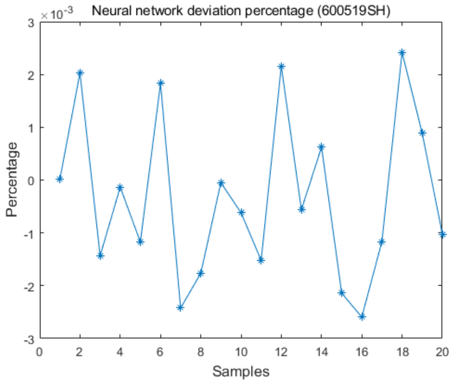
```
clc;

%% Training data and prediction data extraction and normalization
%Load input and output data
%{
src_input=load("000400input.txt");
input_transpose=src_input';
src_out=load("000400output.txt");
output_transpose=src_out';
test_input=load("000400testinput.txt");
input_test=test_input';
test_output=load("000400testoutput.txt");
output_test=test_output';
%}

%{
src_input=load("002281input.txt");
input_transpose=src_input';
src_out=load("002281output.txt");
output_transpose=src_out';
test_input=load("002281testinput.txt");
input_test=test_input';
test_output=load("002281testoutput.txt");
output_test=test_output';
%}



%Load input and output data 600519

src_input=load("600519input.txt");
src_input=src_input(1100:1154,:);
input_transpose=src_input';
src_out=load("600519output.txt");
src_out = src_out(1100:1154,:);
output_transpose=src_out';
test_input=load("600519testinput.txt");
input_test=test_input';
test_output=load("600519testoutput.txt");
output_test=test_output';





%Training sample and input and output data normalization
[inputnet,inputps]=mapminmax(input_transpose);
[outputnet,outputps]=mapminmax(output_transpose);

%% BP network training
%%Initialize the network structure
net=newff(inputnet,outputnet,15);%Create network

net■trainParam■epochs=300; %Set network training index 'epoch'
net■trainParam■lr=0.1;   %Set network training index 'lr'
net■trainParam■goal=0.00001; %Set network training index 'goal'
net■trainParam■show=1000; %Set show interval index 'show'
net■trainParam■showWindow=0; %Set training window visable index 'showWindow'
%Network Training
net=train(net,inputnet,outputnet);

%% BP network prediction
%Prediction data normalization
inputn_test=mapminmax('apply',input_test,inputps);

%Network prediction output
an=sim(net,inputn_test);

%Network output reverse normalization
BPoutput=mapminmax('reverse',an,outputps);

%% Result analysis

figure(1)
plot(BPoutput,':or')
hold on
plot(output_test,'-*');
legend('Predict the output','Expectation output')
title('BP network prediction output (002281SZ)','fontsize',12)
ylabel('Function output','fontsize',12)
xlabel('Samples','fontsize',12)
%Predict the deviation
error=(BPoutput-output_test).*(BPoutput-output_test);
errorpingjun=sum(abs(error))/20

figure(2)
plot(error,'-*')
title('BP network deviation prediction (600519SH)','fontsize',12)
ylabel('Deviation','fontsize',12)
xlabel('Samples','fontsize',12)

figure(3)
plot((output_test-BPoutput)./BPoutput,'-*');
title('Neural network deviation percentage (600519SH)')
ylabel('Percentage','fontsize',12)
xlabel('Samples','fontsize',12)

P_bp = 1- (sum(abs((BPoutput - output_test)))/sum(abs(output_test)))
```

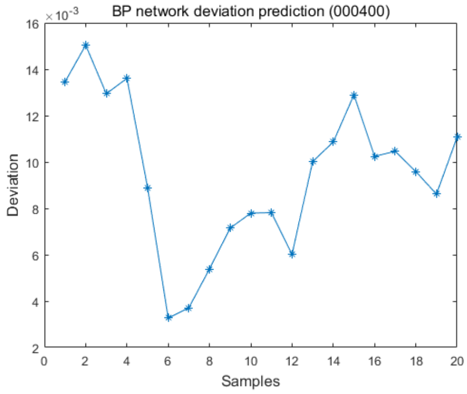
```
clear;
data=load("600519.txt");
index_test = load("600519sg.txt");
%  Read data from txt file
close = data(:,4);
%  Find the upward reversal point
n = length(close);
j = 1;


%{
for T=11:n-5
      if (close(T-5)-close(T))*400/close(T-5) > 4 &&(close(T+5)-close(T))*400/close(T) > 4
            index(j) = T;
            j = j+1;
      end
end
%}



%Upward reversal point judgment model

for T=11:n-5
      if (close(T-10)-close(T))*100/close(T-10) > 3 &&(close(T+5)-close(T))*100/close(T) > 3
            index(j) = T;
            j = j+1;
      end
end




%  Record and save the date when the reversal point appears
n = length(index);
indextwo(1) = index(1);
j=2;
g=2;
for i=2:n
      if (index(i)-index(i-1))>10 %Only record the first occurrence as the reversal point
            indextwo(g) = index(i);
            g = g+1;
            j = j+1;
      end
end

%{
xlswrite('index_test600519',index_test);
xlswrite('indextwo600519',indextwo);
%}

figure(1)
plot(indextwo,':or')
hold on
plot(index_test,'-*');
legend('Predict the output','Expectation output')
title('Stock price rise reversal point prediction output (600519)','fontsize',12)
ylabel('Function output','fontsize',12)
xlabel('Samples','fontsize',12)

P_bp = 1- (sum(abs((indextwo(1:25) - index_test)))/sum(abs(index_test)))
```

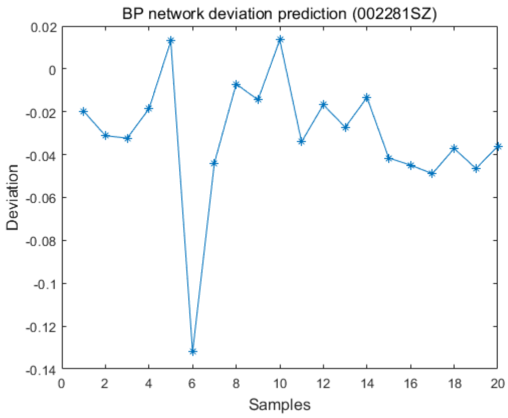
```
clear;
data=load("600519.txt");
index_test = load("600519sg1.txt");
%Find the downward reversal point::
close = data(:,4);
n = length(close);
j = 1;
for T=11:n-5
       if (close(T-5)-close(T))*100/close(T-5) > 3 &&(close(T+3)-close(T))*100/close(T) < 3
             index(j) = T;
             j = j+1;
       end
end

%  Record and save the date when the reversal point appears
n = length(index);
indexthree(1) = index(1);
j=2;

g=2;
%Only record the first occurrence as the reversal point
for i=2:n
       if (index(i)-index(i-1))>10
             indexthree(g) = index(i);
             g = g+1;
             j = j+1;
       end
end

%{
xlswrite('index_test002281t1',index_test);
xlswrite('indextwo002281 t1',indexthree);
%}

figure(1)
plot(indexthree,':or')
hold on
plot(index_test,'-*');
legend('Predict the output','Expectation output')
title('Stock price fall reversal point prediction output (600519)','fontsize',12)
ylabel('Function output','fontsize',12)
xlabel('Samples','fontsize',12)

P_bp = 1- (sum(abs((indexthree(1:25) - index_test)))/sum(abs(index_test)))
```

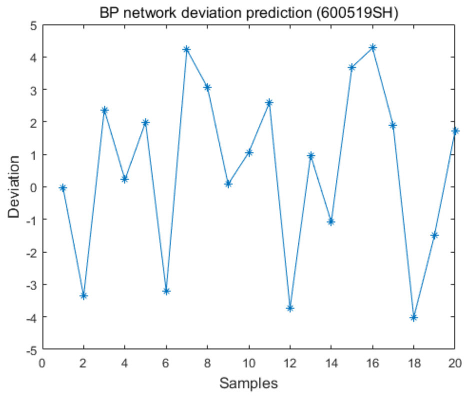

Neural network deviation percentage (000400)
Percentage
Samples


Neural network deviation percentage (002281SZ)
Percentage
Samples


Neural network deviation percentage (600519SH)
Percentage
Samples


BP network deviation prediction (000400)
Deviation
Samples


BP network deviation prediction (002281SZ)
Deviation
Samples


BP network deviation prediction (600519SH)
Deviation
Samples