

The Carbon Trading Price and Trading Volume Forecast in Shanghai City by BP Neural Network

Liu Zhiyuan, Sun Zongdi

Abstract—In this paper, the BP neural network model is established to predict the carbon trading price and carbon trading volume in Shanghai City. First of all, we find the data of carbon trading price and carbon trading volume in Shanghai City from September 30, 2015 to December 23, 2016. The carbon trading price and trading volume data were processed to get the average value of each 5, 10, 20, 30, and 60 carbon trading price and trading volume. Then, these data are used as input of BP neural network model. Finally, after the training of BP neural network, the prediction values of Shanghai carbon trading price and trading volume are obtained, and the model is tested.

Keywords—Carbon trading price, carbon trading volume, BP neural network model, Shanghai City.

I. INTRODUCTION AND LITERATURE REVIEW

CARBON emission has resulted in global climate problems, such as global warming, smog, atmospheric ozone holes, acid rain. These environment problems have caused bad influences on people's health. In order to reduce the carbon emissions, many countries have established carbon trading markets. Carbon finance has attracted more and more people involved into it; therefore, the accurate predictions about carbon price and carbon trading volume will become important for the government and investors.

Hongyu and Xiaodong [1] established a grey system theory model to study the relationship between industrial structure adjustment and carbon emissions. The result showed that the correlation between the third industry and carbon emissions in Shanghai is the largest, and the correlation coefficient between the first industry and carbon emissions in Shanghai is the smallest. They also put forward some suggestions on the development of low carbon economy in Shanghai from the angel of government, enterprise and society.

Min et al. [2] calculated the carbon emissions of 1994-2006 energy consumption in Shanghai, the results show that: Since 1994, carbon emissions increased year by year, and the intensity of carbon emissions continued to decline. The reasons for the decline of carbon emission intensity are analyzed from the aspects of energy efficiency, economic growth, energy structure and economic structure.

Chaohui [3], based on the historical data of Shanghai,

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calculated the quantity of carbon emissions, the evolution trend, per capita carbon emissions and carbon emission intensity. He made research about the relationship among Shanghai energy consumption, economy, population and industrial structure.

Shujiao [4] studied carbon market price forecasting, risk measurement and dynamic behavior around EU, ETS market. For the carbon market price, a multi-scale decomposition algorithm based on improved Hilbert-Huang transform is proposed. Based on the advantages of adaptive data decomposition and artificial intelligence model, the author put forward the price inflection point prediction model based on improved EEMD and support vector machine.

Qingmei [5] took the EU carbon emissions trading market as the research object, selected the factors that affect the price of carbon emission rights, through the establishment of BP neural network model to analyze the data and get the weight of the impact factors. After analyzing the data, the weight of influencing factors were obtained. Finally, she reached the conclusion that policy and energy factors had the greatest influence on the price of carbon emissions, and that the temperature had little effect on the price of carbon emissions.

Fen [6] took Shanghai city as the research object, based on the data of the statistical yearbook of Shanghai city in 2003-2012. The carbon emissions of Shanghai city were analyzed and estimated from the view of carbon source and carbon sink. Taking the two provinces and one city along the Yangtze River Delta as the comparison object, Zhou Fen analyzed the regional carbon emissions and explained the characteristics of carbon emissions in Shanghai. The KAYA identity was used to forecast the future trend of carbon emissions in Shanghai, and suggestions were put forward for the low-carbon development of Shanghai.

Dedong [7] took EU carbon market as the research sample, studied the dependence structure and Risk Spillover Effect of the carbon market. Based on this, he further studied their influence on the price of carbon emissions.

Tingting et al. [8] took Beijing, Shanghai, Shenzhen, Tianjin and Hubei carbon emissions exchange rate as the study object, adopted different quantile regression models to measure and examine the carbon financial risk level. Finally, they arrived at the conclusion: QAR-GARCH model is more suitable for China's carbon financial market risk characterization than CAViaR family model. The carbon finance market in China is in the developing stage, and among the five carbon markets, the maturity of Shenzhen market is the highest, and the maturity of Hu Bei carbon market is the lowest.

II. BP NEURAL NETWORK

Artificial neural network (ANN) is an abstract mathematical model which reflects the structure and function of human brain, proposed and developed based on modern neuroscience [9]. ANN has been widely used in pattern recognition, image processing, intelligent control, combinatorial optimization, financial forecasting and management, communication, robotics and expert systems.

BP neural network (BPNN) is a multilayer feedforward network trained by error back-propagation algorithm, which is one of the most widely used neural network models. BPNN can learn and store a large number of input-output mapping relationships, without the need to reveal the mathematical equation describing the mapping relationship. The BPNN is widely used in the field of prediction, image processing, pattern recognition and so on [10].

III. MODEL ESTABLISHMENT

The BP neural network consisted of an input layer, an output layer and several intermediate layers.

- Determine input variables: We take the average values of the Shanghai carbon trading price and the Shanghai carbon trading volume for each continuous 5 days, 10 days, 20 days, 30 days, 60 days as the input variables.
- Determine output variables: We take Shanghai carbon trading price and Shanghai carbon trading volume as the output variables.
- Determine the number of hidden nodes: The number of hidden nodes has a great influence on the convergence speed and precision of BPNN. We use the trial and error method to determine the optimal number of hidden nodes, and the number of nodes with the best performance is selected as the number of hidden layer neurons. The BPNN model is established as Fig. 1.

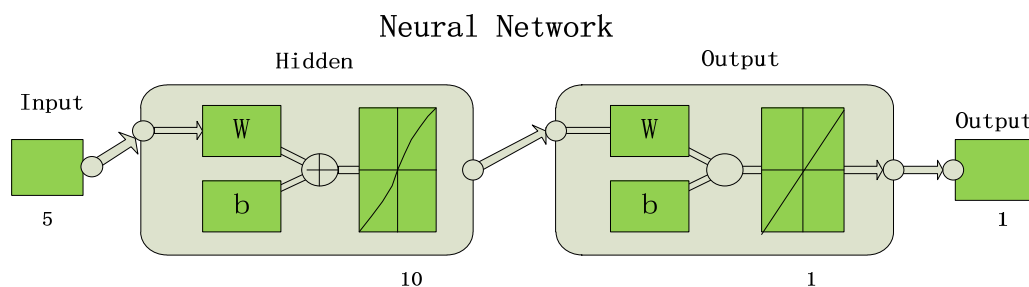


Fig. 1 BP neural network model

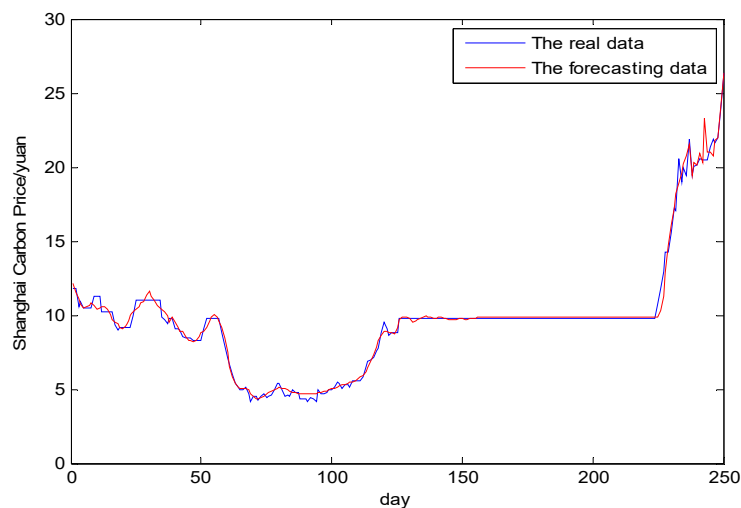


Fig. 2 Shanghai carbon trading prices forecasting and the real data

IV. MODEL RESULTS AND TESTING

A. Data Collection

We adopt the data of Shanghai carbon trading price and Shanghai carbon trading volume between 2015-9-30 and 2016-12-23.

B. Data Handling

The data were processed to get the average value of every 5

days, 10 days, 20 days, 30 days, 60 days, respectively. The input data are normalized, trained and simulated to obtain the output data, and the output data are reduced to the original order of magnitude.

C. Results

(1) The Forecasting Result of Shanghai Carbon Trading Prices

As we can see from Fig. 2, the forecasting data curve is

close to the real data curve, and we can also get the next following forecasting carbon price data.

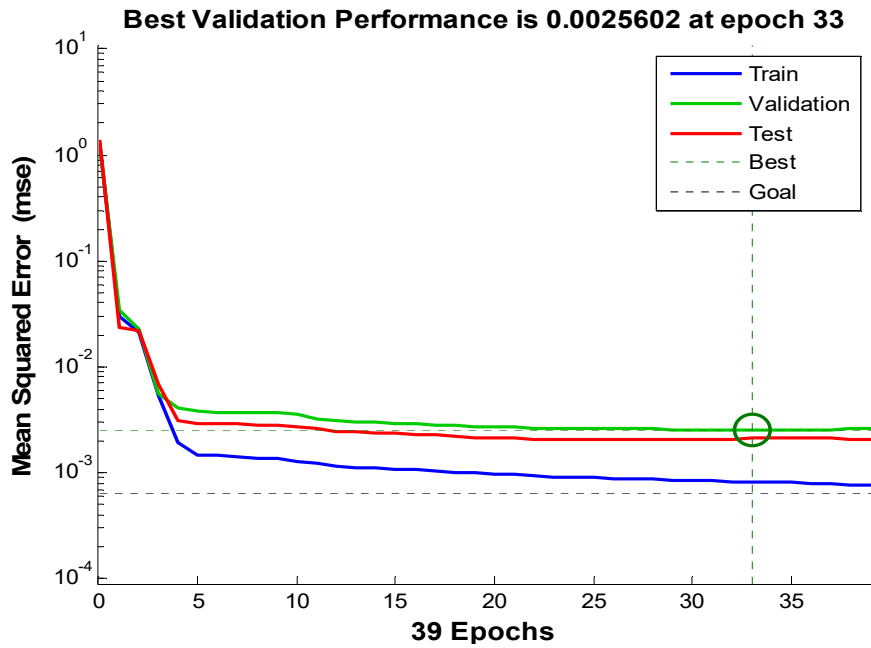


Fig. 3 (a) The optimal validity test

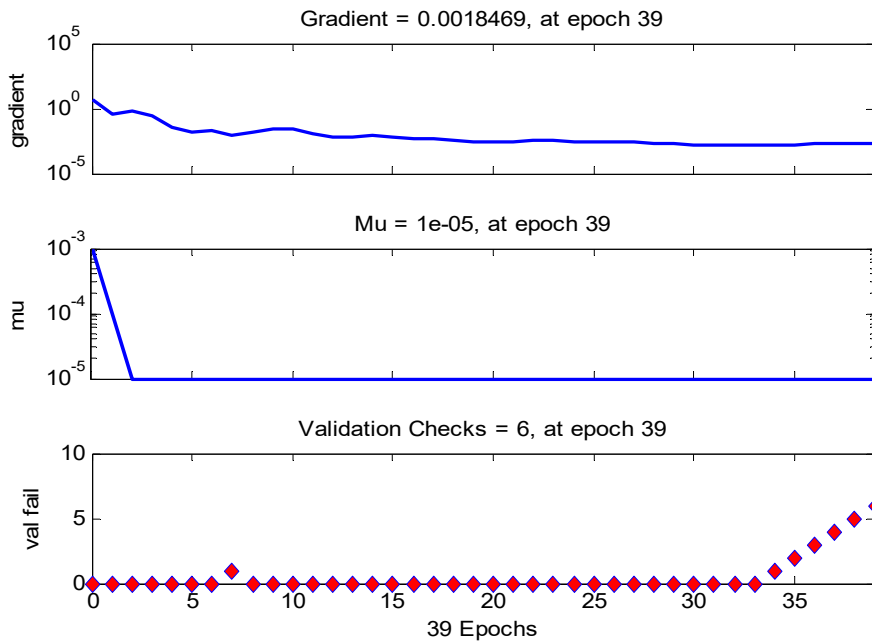


Fig. 3 (b) The optimal validity test

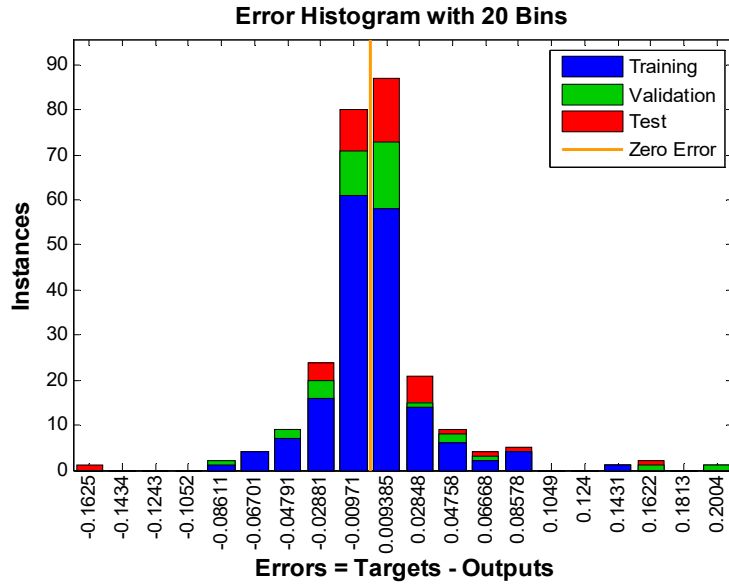


Fig. 3 (c) The optimal validity test

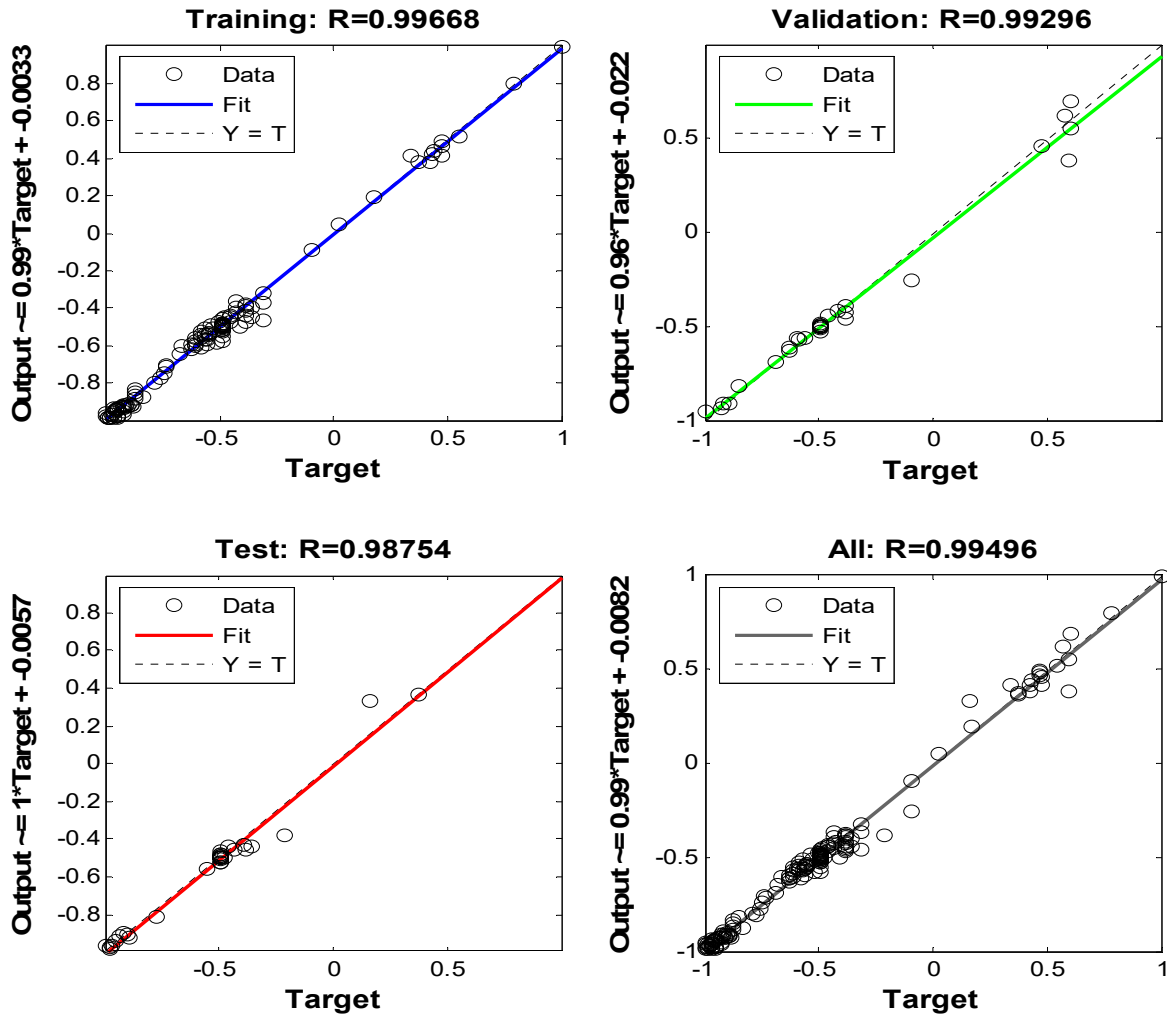


Fig. 4 The fitting test

From the optimal validity test, Fig. 3, the simulation results show that the dashed line and the expected results of the blue and green lines are basically fit. From the fitting test, we can find that the fitting effect is very good. Therefore, the model testing result shows the BP neural network is very effective.

(2) The Forecasting Result of Shanghai Carbon Trading Volumes

From Fig. 5, we can find that the forecasting data line is close to the real data, this explains the fitting effect is good, and the model testing result is as is Figs. 5-7.

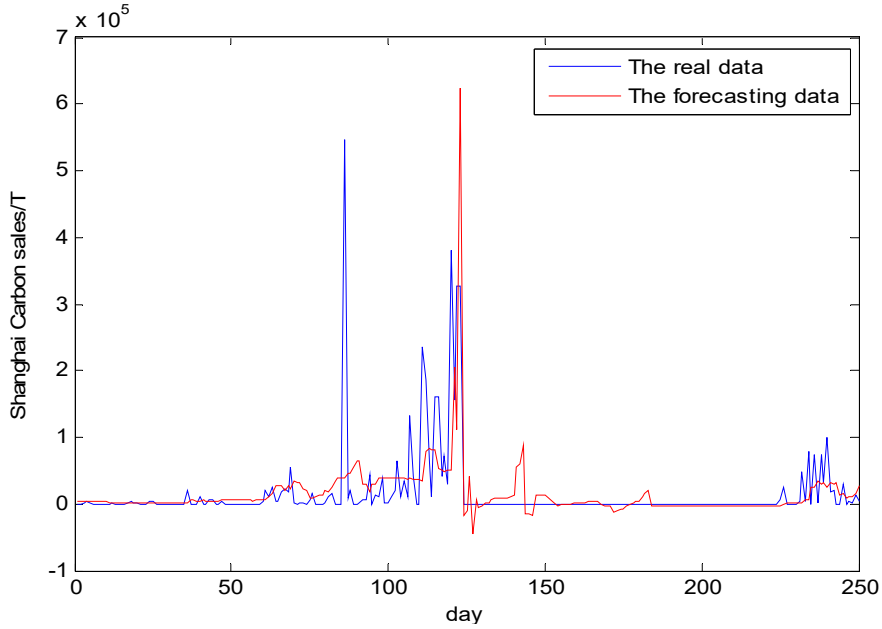


Fig. 5 Shanghai carbon trading volumes forecasting and the real data

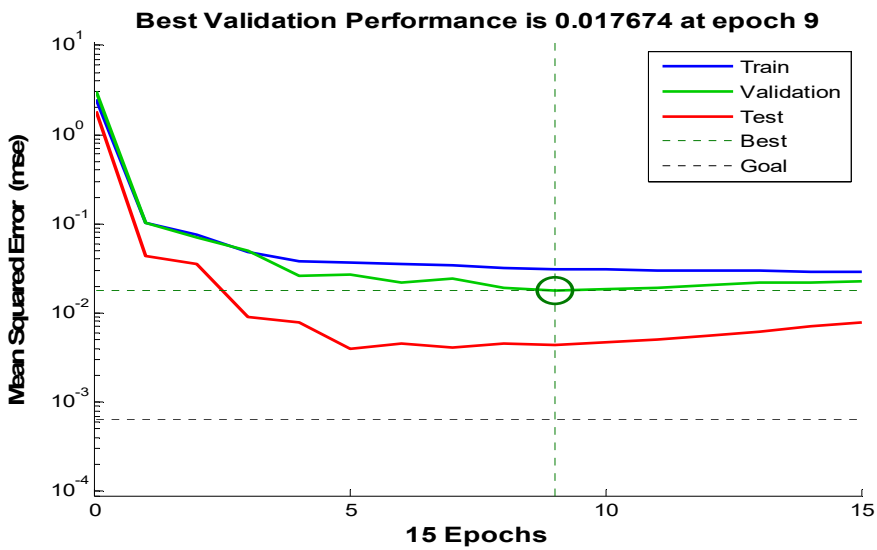


Fig. 6 (a) Shanghai carbon trading volume optimal validity test

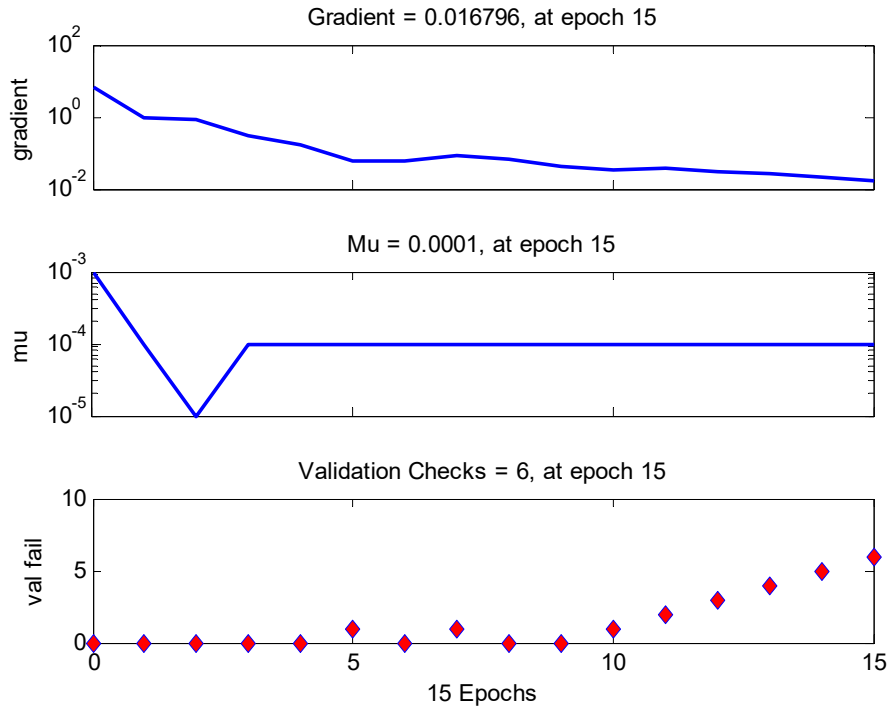


Fig. 6 (b) Shanghai carbon trading volume optimal validity test

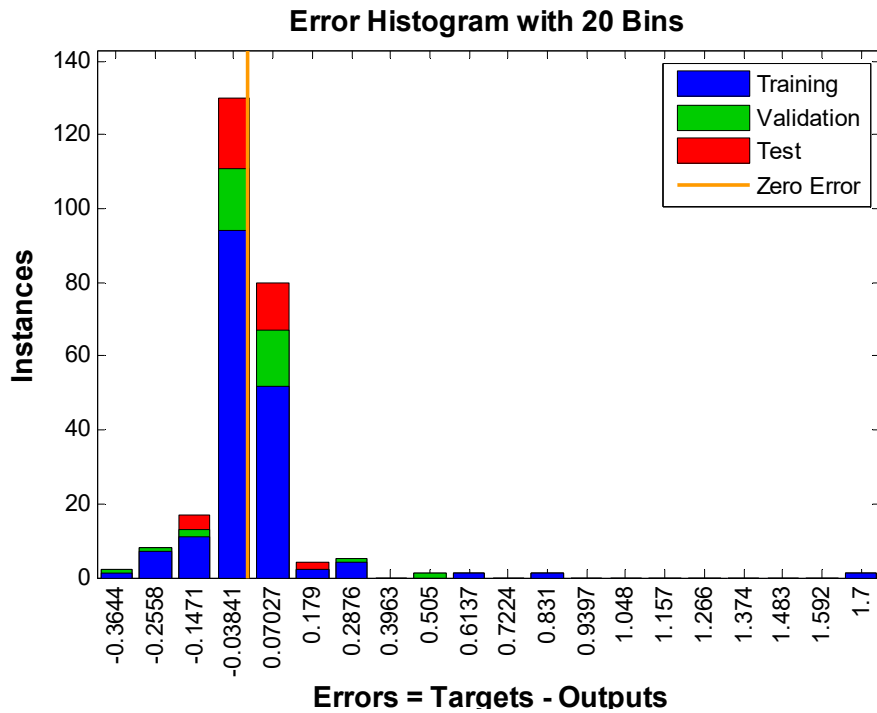


Fig. 6 (c) Shanghai carbon trading volume optimal validity test

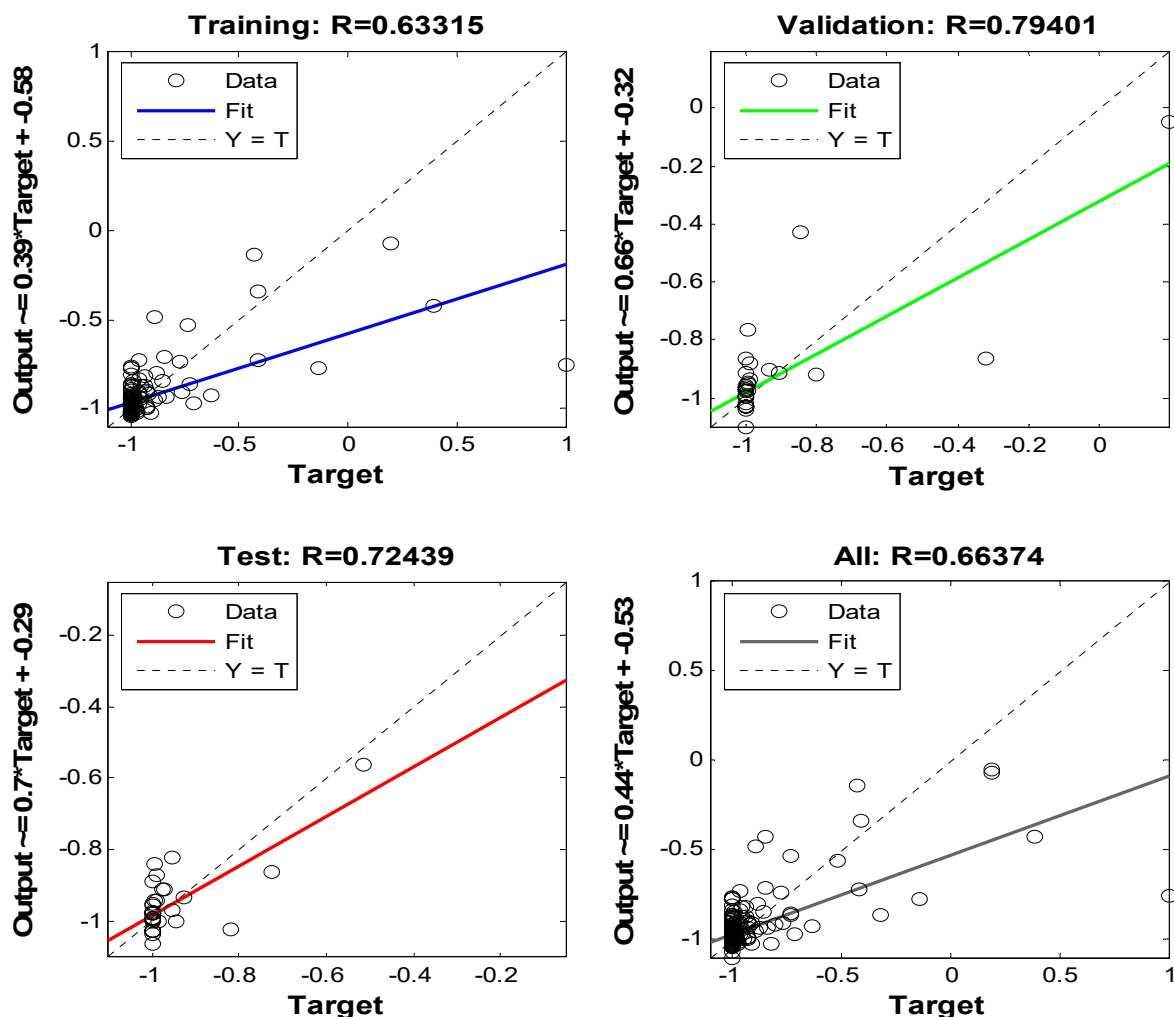


Fig. 7 The Shanghai carbon trading volume fitting line

From Fig. 6, we can find that the dashed line and the expected results of the blue and green lines are basically fit, the validation line is close to the train line and test line. From Fig. 7, we can find the fitting lines pass through more points. Therefore, the BP neural network effect is very good.

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