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Carbon Price Prediction based on Genetic Algorithm Optimized BP Neural Network

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Abstract: With the launch of the carbon emissions trading system, the prediction of carbon prices provides a basis for those in power to formulate relevant policies and provides potential risk mechanisms for carbon market participants. Aiming at the disadvantages of the traditional BP neural network that the convergence speed is slow and it is easy to fall into the local extreme value, this paper constructs a carbon price prediction model based on the genetic algorithm to optimize the BP neural network, which can predict the carbon price quickly and accurately. Through analysis of primary and secondary factors, coal prices, oil prices, natural gas prices, and electricity prices are selected as the input to the network. The initial weights and thresholds obtained by the genetic algorithm search can accurately predict the carbon price. Through the relevant verification of the test data, the accuracy and stability of the BP neural network carbon price prediction model optimized by the genetic algorithm have reached expectations.

Keywords: Factor; Carbon price; Genetic algorithm; BP neural network

1 Introduction

With the Industrial Revolution, environmental problems such as air pollution, melting glaciers, and excessive carbon dioxide emissions have become increasingly severe. Extreme weather events caused by global warming have become new threats to the security of the international community. Therefore, mankind needs to cooperate more closely to jointly deal with environmental problems. In terms of controlling greenhouse gas emissions, the European Union and other developed countries acted earlier and established the first carbon emissions trading system (EU-ETS), which aims to limit the upper limit of greenhouse gas emissions that companies in various countries can emit. In the carbon finance market, the carbon price (carbon emission price) is an intangible asset that is traded in the market like other commodities [1]. Therefore, accurate carbon emission price forecasts not only provide effective basis for the government to formulate relevant policies, but also provide potential risk mechanisms for individual investors to participate in the carbon financial market [2].

Although there are many methods for studying carbon trading price prediction, the main method can be divided into carbon trading price prediction based on influencing factors or based on historical data [3, 4].Research on carbon trading prices based on influencing factors is to determine the main factors affecting carbon prices through certain models or methods. If necessary, adjust the price of carbon trading by adjusting relevant factors. For example, Tsai et al. [5] proposed a carbon price prediction system considering the influence of multiple factors. This method uses data such as carbon trading prices, oil prices, coal prices, and natural gas prices as the carbon price influence factors, and uses radial basis function neural networks (RBFNN) to obtain the best parameters so that the learning rate can adjust and improve the prediction error during the training process. Zhao et al. [6] proposed a method of real-time prediction of weekly carbon prices using multiple factors with different sampling frequencies, and created a combined model of five weighting schemes to evaluate the prediction accuracy. Another research method of carbon trading price prediction based on historical data

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is mainly to use historical data to establish a model to predict carbon trading prices. For example, Atsalakis et al. [7] proposed three computational intelligence technologies, in which a hybrid neuro-fuzzy controller was applied to carbon price prediction, and accurate prediction results were obtained.

Carbon trading price is a non-linear, non-stationary and violent fluctuation time series data. It is affected by various factors. Obviously, the above two methods cannot well grasp the trend of carbon price. This article analyzes the primary and secondary relationship of influencing factors, discarding the constant factors throughout the year, and combines deep learning algorithms to predict carbon prices, providing a new method for carbon price prediction.

2 Carbon price prediction model

2.1 Structured data selection based on influencing factors

There are many factors affecting the price of carbon trading, but most of them are related to the use of fossil energy, and the demand for fossil energy depends on their absolute and relative prices. Among fossil energy sources, coal, oil and natural gas account for 80% and have the most impact on carbon prices [8]. In addition, the burning of fossil fuels has many connections with power companies. At present, the main fuel for power generation by power companies is still fossil fuels. Therefore, it is necessary to study the relationship between electricity prices and carbon prices.

2.2 BP neural network model optimized by genetic algorithm

The basic principle of BP neural network is the gradient steepest descent method. The idea is to continuously adjust the weights to make the objective function reach the minimum. However, it also has shortcomings such as oversaturation and falling into a local minimum, which can be effectively solved by optimizing the initial weight and threshold of the BP neural network through genetic algorithm [9, 10]. Due to the obvious non-linear characteristics between the carbon price and the parameter value, this paper uses the BP neural network optimized by the genetic algorithm as the basic method of carbon price prediction. Relevant research shows that a neural network with a hidden layer can approximate any nonlinear function as long as there are enough points in the hidden layer [11, 12]. Therefore, this article uses a three-layer multi-input single-output BP neural network with a hidden layer. The coal price, oil price, natural gas price and electricity price are used as the input layer of the neural network, and the carbon price is used as the output layer of the neural network. The number of hidden layer nodes is selected as 6 based on experience and many experiments. Combining the characteristics of the data, each hidden layer and the output layer select an appropriate activation function. The activation function of each hidden layer selects a logistic function [13], and the activation function of the output layer selects a linear function [14]. The structure diagram of this neural network is shown in Fig. 1.The genetic algorithm is used to optimize the initial weights and thresholds of the BP neural network to obtain the optimal individual weights and thresholds.

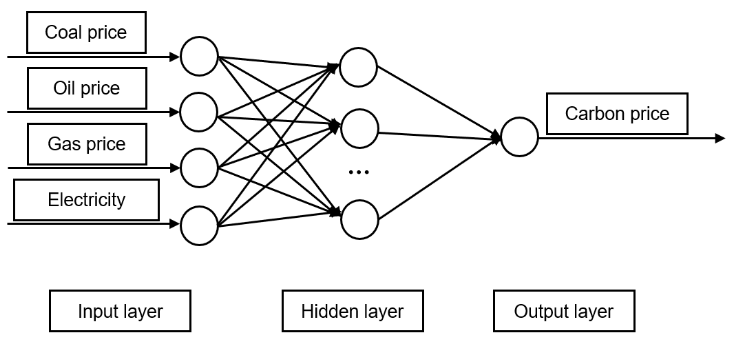

Figure 1: The structure diagram of BP neural network

For the evaluation indicators of the neural network model, the root mean square error (RMSE) and the mean absolute error (MAE) of the sample prediction results are mainly selected. The root mean square error and mean absolute error are defined as follows.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}^{(i)} - y^{(i)})^2}{n}} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}^{(i)} - y^{(i)}| \tag{2}$$

Where n is the number of monitoring samples, $\hat{y}^{(i)}$ is the predicted value of the ith sample by the neural network, and $y^{(i)}$ is the expected value of the ith sample. Obviously, the smaller the value of RMSE, the higher the prediction accuracy of the model, and the value of MAE can truly reflect the actual situation of the prediction error.

3 Result and discussion

This article uses the EUA futures prices due in December 2018 announced by the European Energy Exchange as the main body of the research [15]. Among various influencing factors, energy prices occupy a very important position, and coal prices, oil prices, natural gas prices, and electricity prices are used to reflect their energy prices. The representative variables and data sources are shown in Table 1.

Table 1: Representative variable meaning and data source

Variable name	Variable symbol	Variable meaning	unit	Data Sources
Coal price	COAL	EU thermal coal spot prices	USD/ton	Wind
Oil price	OIL	British Brent crude oil futures	USD/barrel	ICE
Natural gas	GAS	British natural gas futures prices	Pounds per thermal unit	ICE
Electricity price	EPRI	Basic European Power Index	Euro/MWh	European Exchange
EUA spot price	EUA0	EU thermal coal spot prices	Euro/ton	EEX

The obtained sample data is divided into two parts, namely training data and test data, as shown in Table 2. The training data is used to train the neural network to update the threshold and weight. The test data is used to check the accuracy of the model and ensure the accuracy of the results.

Table 2: The data sets for all studies cases

Case	Training Data	Training Data(year/date)	Test Data(year/date)
1	Similar days of Monday in spring	2010 2017 Monday in spring	2018 Monday in spring
2	Similar days of weekday in spring	2010 2017 01.01 03.30	2018.01.01 2018.03.30

Table 3 shows the RMSE and MAE of all the research cases, indicating that using the influencing factors as the input of the neural network can effectively improve the accuracy of the carbon price prediction model. Using genetic algorithm to optimize the parameters of the BP neural network algorithm can get a smaller RMSE MAE shows that genetic algorithm optimization of BP neural network can improve stability and accuracy. Figure 2(a)(b) shows carbon price forecasts for various cases. It can be seen from the figure that the predicted result is very close to the actual carbon price, and there is a good agreement, indicating that the BP neural network optimized by the genetic algorithm has improved the previous local optimization characteristics to a certain extent.

Table 3: RMSE and MAE of two research cases

Case	No. of training data	No. of test data	RMSE	MAE
1	84	12	0.092	0.191
2	462	26	0.119	0.185

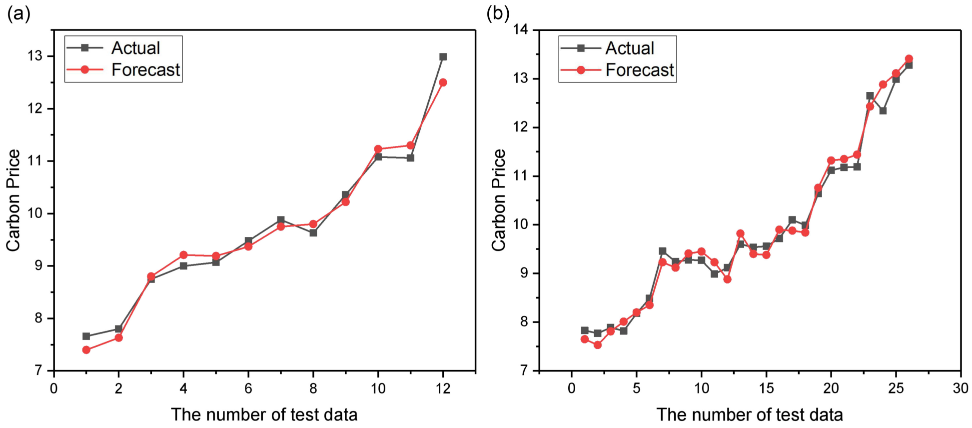

Figure 2: Carbon price prediction in various cases (a) Case 1 and (b) Case 2

4 Conclusions

In this paper, the main influencing factors of the carbon price are screened out by analyzing the factors that affect the carbon price, and the genetic algorithm is introduced to optimize the BP neural network to predict the carbon price in similar seasons. Using genetic algorithm to optimize the BP neural network can handle the complex relationship between nonlinear data, and use the actual data of EU-ETS to verify the accuracy of the model. The RMSE and MAE values of the two cases show that the genetic algorithm optimizes the BP neural network with high accuracy. Therefore, this model provides a feasible method for carbon price prediction.

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