Analysis of Factors Influencing Carbon Price Based on Graph Neural Network

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Abstract. Due to greenhouse gas emissions caused by fossil energy use, it is urgent to reduce carbon emissions. The carbon market is a powerful tool for emission reduction, and the analysis of the relationship between carbon price and energy price is of great significance to the reasonable formulation of carbon price and the healthy operation of carbon market. Based on time convolutional network, transfer entropy matrix and graph attention network, the paper establishes a graph neural network model that can analyse the influencing factors of carbon price. Based on the data of carbon price, electricity price, natural gas price, oil price and temperature in China, the causal relationship and influence between carbon price and other factors are analysed, and the graph network structure with weights of carbon price and other factors is obtained.

Keywords: carbon market, carbon price, graph neural network, transfer entropy, influence analysis.

1 Introduction

With the rapid development of the world economy and the acceleration of industrialization, carbon dioxide emissions are increasing year by year, which may lead to a continuous increase in global temperature. Faced with the threat of ecological damage and climate anomalies, reducing and controlling carbon emissions has become a worldwide consensus. The carbon trading mechanism has played an important role in the world's carbon emission reduction project. The carbon price is the core element of carbon market. Therefore, it is of great significance to analyse the causality and influencing factors of carbon price.

In recent years, neural networks have been widely used for feature extraction and influence analysis of data. Traditional deep learning methods have achieved great success in extracting the features of Euclidean spatial data, but its performance in processing non-European spatial data is still unsatisfactory. Graph neural network (GNN) makes up for this shortcoming well. GNN is a connection model that obtains the dependency relationship in the graph through the information transmission between nodes in the network [1]. GNN combine node feature information with the graph structure by recursively passing messages along edges of the input graph [2].

In recent years, GNN have been developed greatly and are widely used in data analysis. Sanjay Kumar et.al [3] propose a novel method of influence maximization based on GNNs. Qi

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Cao et.al [4] used GNNs to predict the popularity of content on social networks. Jiyong Zhang et.al [5] used GNNs for point of interest recommendation and achieved good results. A physics-inspired data-driven model based on GNNs is proposed to estimate the power output of wind turbines [6].

Based on time convolution module, transfer entropy matrix and graph attention network, a graph neural network model is established to analyse the influencing factors of carbon price in the paper. Based on the carbon price, electricity price, natural gas price, oil price and temperature in China, the causal relationship and influence between relevant factors and the carbon market are analysed, and the network correlation diagram with weights between carbon price and other factors is obtained.

2 Method

2.1 Temporal convolutional network

The time convolution network (TCN) is mainly used for feature extraction of time series values as node features of graphs. TCN is a special convolutional neural network [7], which does convolution for one-dimensional space and iteratively captures long-term relationships at multiple layers. As the figure 1, for the value at time t of the previous level, which only depends the value at time t of the next level and the value before it. Different from traditional convolutional neural networks, TCN cannot see future data, and it is a unidirectional structure, not bidirectional. That is to say, only with the preceding cause can there be the following effect, which is a strict time constraint model.

TCN combines extended convolutional network and causal convolutional network to obtain faster time series data processing ability. Compared with ordinary convolutional network, TCN has larger receptive field and can extract more load features in sequence data.

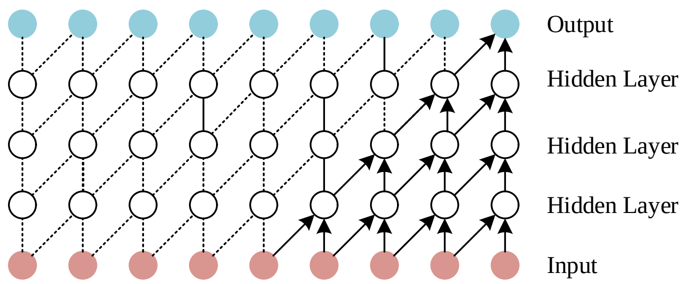


Figure 1. The temporal convolutional network framework

2.2 Transfer entropy

Transfer entropy is an entropy function that measures the coupling relationship and the information transfer relationship between different time series. The transfer entropy is used to quantify the causal relationship between various factors and changes of carbon price. According to the comparison of the positive and negative directions of transfer entropy, the causal relationship between each factor is constructed. When variable y changes from unknown to known, the increase in the information content of variable x is the transfer entropy from y to x, which is expressed as follows according to the transfer entropy [8].

$$T_{y\rightarrow x}\left(x(1)\middle|x^{(k)},y^{(l)}(\tau)\right) = \int p\left(x(1),x^{(k)},y^{(l)}(\tau)\right)\log_2\left\{\frac{p\left(x(1),x^{(k)},y^{(l)}(\tau)\right)}{p(x(1),x^{(k)})}\right\}dx(1)dx^{(k)}dy^{(l)} \tag{1}$$

$T_{y\rightarrow x}$ denotes the transfer entropy of y to x, and k and l denote the orders of x and y, respectively.

In order to simplify the calculation difficulties caused by complex high-dimensional density functions in the process of transfer entropy calculation, assume that both processes x and y are first-order Markov processes, that is, k=l=1. The calculated variance of transfer entropy is simplified as follows [9,10].

$$T_{y\rightarrow x}\left(x(1)\middle|x^{(k)},y^{(l)}(\tau)\right) = \frac{1}{2}\log_2\left\{\frac{\left(\rho_{xy}^2(\tau)-1\right)\left(\hat{R}_{xx}^2(1)-1\right)}{2\rho_{xy}(\tau-1)\hat{R}_{xx}(1)\rho_{xy}(\tau)-\rho_{xy}^2(\tau-1)-\hat{R}_{xx}^2(1)-\rho_{xy}^2(\tau)+1}\right\} \tag{2}$$

Where

$$\hat{R}_{xx}^2(\tau) = \frac{R_{xx}(\tau)}{R_{xx}(0)} \tag{3}$$

$$\rho_{xy}(\tau) = \frac{R_{xy}(\tau)}{\sqrt{R_{xx}(0)R_{yy}(0)}} \tag{4}$$

$$R_{xy}(\tau) = E[x(n)y(n+\tau)] \tag{5}$$

R_{xx} and R_{yy} represent the autocorrelation coefficients of x and y; ρ_{xy} represents the linear cross-correlation function of x and y.

2.3 Graph attention network

Graph attention network is a graph convolutional network formed by applying attention mechanism to graph convolutional network. In the traditional graph convolutional network, the confidence weight of the adjacency matrix is constant. The introduction of attention mechanism enables graph neural network to assign different importance to different edges, so as to quantitatively describe the influence of different adjacent nodes. Compared with traditional graph convolutional network, graph attention network has the advantages of simple calculation and allowing to set weights for adjacent nodes. The objective function of graph attention network is:

$$h_i^t = ||_{k=1}^K \sigma\left(\sum_{j\in N_i} \alpha_k\left(h_i^{t-1}, h_j^{t-1}\right) W_k^{t-1} h_j^{t-1}\right) \tag{6}$$

h_i is the feature aggregation function of the node i; α_k *and* W_k denote the confidence and weight matrices, respectively.

2.4 The framework of Graph neural network model

The framework of Graph neural network model as Figure 2. Firstly, the data is divided into node data and graph structure data. Secondly, for the node data, the node feature matrix is constructed while reducing the dimension through time convolution, and the transfer entropy is calculated as the node adjacency matrix. For the graph structure data, the attention network is introduced to establish the correlation weight network. Then graph structure is used as the input data of the graph convolutional neural network, node feature data passed through the graph structure is output. The characteristic data of each node is arranged according to the time sequence, and the sequence residual is calculated by using the predicted value of the output and the actual value to optimize the network structure of the graph, and finally the graph network structure with weight is obtained.

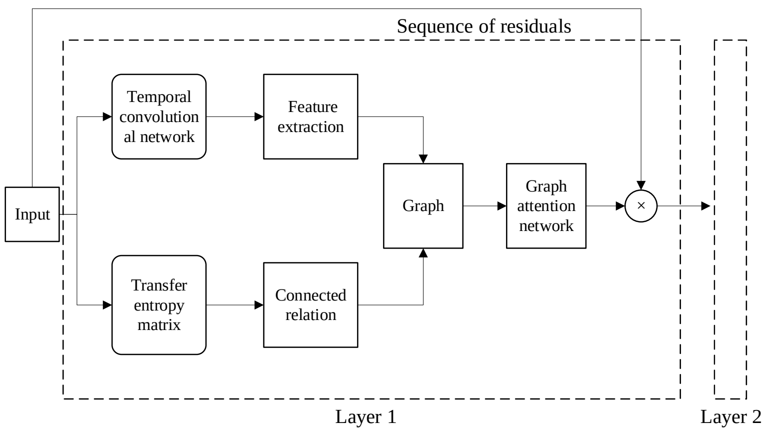


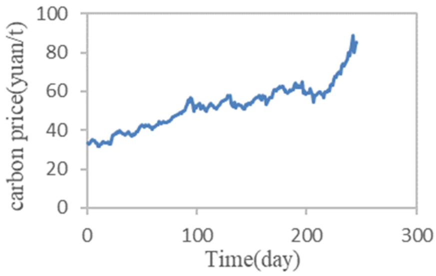
Figure 2. Analysis model of influencing factors of carbon price based on graph neural network

3 Case study

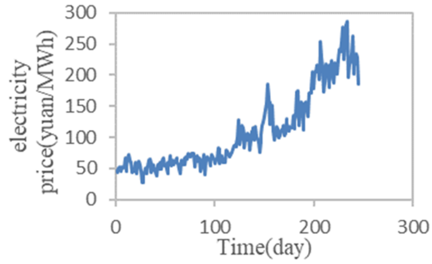
Causality analysis and mining are carried out for historical data such as carbon price, electricity price, natural gas price, oil price and temperature.

3.1 Data pre-processing

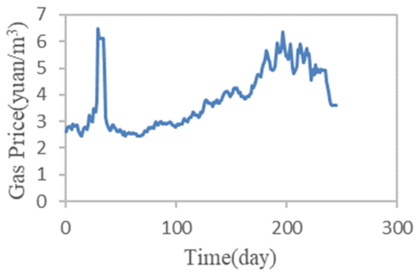
The cleaning of carbon price, electricity price, oil and gas price and weather data mainly includes the elimination of erroneous data and the unification of missing signs. For the anomaly test, the 3σ test is used to process 245 sets of data. The data after data pre-processing as Figure 3.



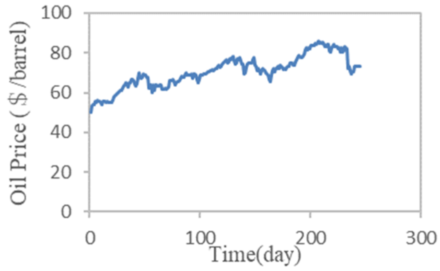
(a) Carbon ptice



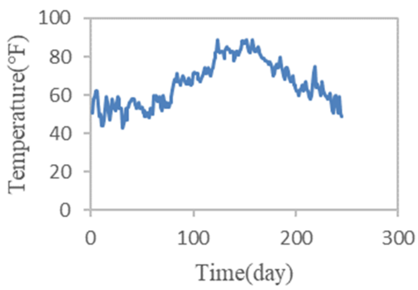
(b) Eletricity price



(c) Gas price



(d) Oil ptice

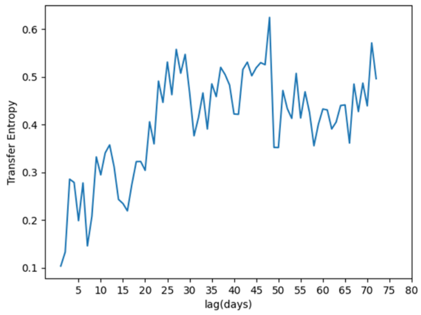


(e) Temperature

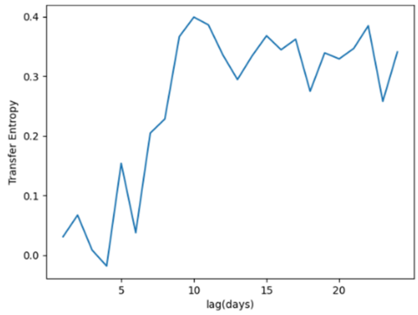
Figure 3. The curves of carbon price, energy prices and temperatures over time

3.2 Causality analysis based on transfer entropy

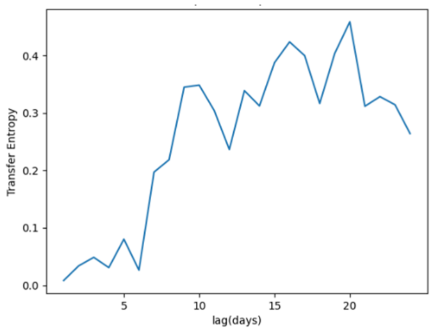
The transfer entropy is used to quantify the causal relationship between various factors and changes of carbon price, and accurately measure the amount of information transmission to the carbon price. From the measurement results in Figure 4 of the correlation degree between carbon price and other factors, it can be seen that the direction of the correlation relationship is obvious, and the difference is basically between 0.2 and 0.5, which indicates that temperature, electricity price, oil price and natural gas price are all the reasons affecting the price of carbon.



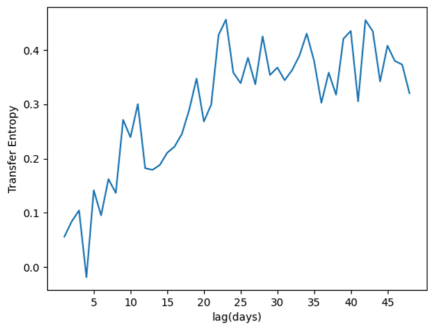
(a) Transfer entropy between carbon price and electricity price



(b) Transfer entropy between carbon price and gas price



(c) Transfer entropy between carbon price and oil price



(d) Transfer entropy between carbon price and temperature

Figure 4. Entropy of transfer between carbon price and other factors

3.3 Influential weights of carbon price and other factors

Based on the self-extracted network structure of carbon market influence factors, a two-layer neural network model was constructed. The results show that carbon price is affected by natural gas price, electricity price, oil price and temperature at the same time, and temperature has the largest weight. This may be because temperature has a significant impact on the overall energy consumption demand of society, while carbon price is mainly affected by carbon emissions caused by energy consumption. In addition, oil prices also have a large impact on natural gas prices, which may be due to the linkage mechanism between natural gas pricing and oil prices in the Asia-Pacific region. In addition, electricity price only has an obvious impact on carbon price, but has no obvious impact transmission with other energy commodities.

4 Conclusion

This paper calculates the transfer entropy between carbon price and other factors, and analyses the correlation between carbon price and other factors based on the graph neural network model. According to the transfer entropy results, it can be seen from the results obtained by measuring the correlation degree between carbon price and other factors that the difference is basically between 0.2-0.5. Therefore, temperature, oil price, natural gas price and electricity price are the factors that affect the carbon price. The graph network structure obtained by training shows carbon price is affected by natural gas price, electricity price, oil price and temperature at the same time, which is moderate with the analysis result of transfer entropy. The graph network structure with weights show that temperature first affects the price of the energy commodity, and then the energy commodity price transmits the impact to the carbon price, while the change of the primary energy price is able to pass on to the secondary energy.

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