Article

Carbon emission allowance price forecasting for China Guangdong carbon emission exchange via the neural network

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Abstract: Carbon emission allowance price forecasting is a significant issue for policy makers and investors with the world transitioning to green energy and devoting enormous efforts to be more sustainable. This study explores usefulness of the nonlinear autoregressive neural network for this forecasting problem in a dataset of daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange during 19 December 2013–20 August 2021. Through examining various model settings across the algorithm, delay, hidden neuron, and data splitting ratio, the model leading to generally accurate and stable performance is reached. Usefulness of the machine learning technique for the price forecasting problem of the carbon emission allowance price is illustrated. Results here might be used on a standalone basis as technical forecasts or combined with fundamental forecasts to form perspectives of price trends and perform policy analysis, which could better assist different stakeholders in understanding energy cost and planning for green transition.

Keywords: carbon emission allowance; China Guangdong Carbon Emission Exchange; price forecasting; time series; neural network

1. Introduction

Carbon emission allowance price forecasting is a significant issue for policy makers and investors. Because of irregular price volatilities [1–8], great influences on decision making processes, and hence on resource allocation and economic welfare [9,10], significance of their price forecasts to the society might need little motivation.

A great amount of previous studies [9–67] have concentrated on a wide variety of (time series) econometric models, expert forecasts, commercial services, and so forth for price forecasts. Econometric models often seen in the literature include the autoregressive moving average [11,13,17,19,21,25,27,29,31,33,35,37,52], vector autoregressive [9–11,23,27,29,31,33,39–48,53], vector error correction [9,10,39,43,49–51,55,68–70], and a diverse variety of their variations.

Recently, machine learning approaches [71–74] have shown their great potential for forecasting allocations [75–77] and prices [78–130] related to carbon emission allowances. Machine learning techniques often seen in the literature include the neural network [82,88,89,92,96,97,99,100,102,104,106,107,111,112,117,118,120,122,123,126,128–130], extreme learning [83,87,90,91,98,100,101,103,107–110,119,124], support vector regression [84,86,105,111,113,115,116,121,122,125], fuzzy stochastic model [85], ensemble learning [93–95,98,127], decision tree [104], random forest [111], boosting [111,120,126], bagging [126], and Bayesian network [114]. In particular,
previous studies have shown that the neural network technique has great potential for forecasting economic and financial time series, which generally tend to be highly noised and chaotic [131–142]. Previous research has also shown that the neural network technique could lead to high accuracy under different forecast settings [133,135,137,141,143–150]. This can benefit from capabilities of self-learning of the neural network for forecasting [139,151,152] and capturing nonlinearities [153–155] often inhabiting in economic and financial time series data. One greatest advantage of the neural network as compared to other nonlinear methods for time series data is that a class of multilayer neural networks could well approximate a large class of functions [133,135,137,156,157]. The present study will concentrate on the neural network for forecasting carbon emission allowance prices.

To facilitate analysis, the forecasting problem in a dataset of daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange during 19 December 2013 to 20 August 2021 is investigated via the nonlinear autoregressive neural network. By examining various model settings across the algorithm, delay, hidden neuron, and data splitting ratio, the model leading to generally accurate and stable performance is arrived at. The present work, to authors’ knowledge, is the first one that adopts the machine learning techniques for modeling the particular daily closing prices of carbon emission allowances for the Chinese market, which carries significant economic values not only domestically but also from a global perspective. Understandings of price trends and movements of financialized energy indices have important implications for decision makings for the efforts of green energy transition for policymakers. Results here could be used on a standalone basis as technical forecasts or combined with fundamental forecasts to form perspectives of price trends and perform policy analysis. This could better assist different decision markers in understanding energy cost trends and future movements and planning for green transition. As prices of the carbon emission allowances are rather irregular that could make forecasting difficult, the neural network proposed in the present study demonstrates great potential for tackling this issue through achieving accurate and stable forecasting results that could be consumed by various forecast users. The forecasting framework might also be generalized to related forecasting problems for other relevant energy and resource price forecasting exercises as part of understanding different phases of green transition.

2. Data

Daily closing price (RMB/Ton) data of carbon emission allowances traded in China Guangdong Carbon Emission Exchange during 19 December 2013–20 August 2021 for analysis are sourced from Wind Information Co., Ltd. And plotted on the top panel of Figure 1, together with their first differences. The bottom panel of Figure 1 also visualizes the prices and their first differences with histograms of fifty bins and kernel estimates to present the distributions. Table 1 reports summary statistics of the data, where one could see that they are not normally distributed, as generally expected for financial series [158–163]. The BDS (Brock, Dechert and Scheinkman) test shows that nonlinearities inhabit the price series, suggesting that the neural network model could potentially serve as a good choice for building the price forecast model.
Figure 1. Daily closing prices (black line) and their first differences (grey line) of carbon emission allowances traded in China Guangdong Carbon Emission Exchange (top panel) and histograms with fifty bins and kernel estimates of the prices (bottom left panel) and their first differences (bottom right panel).

Table 1. Summary statistics of daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange.

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Standard deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque-Bera p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>8.1000</td>
<td>23.4634</td>
<td>20.2000</td>
<td>77.0000</td>
<td>12.3267</td>
<td>1.7543</td>
<td>6.3731</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>First difference</td>
<td>−9.9800</td>
<td>−0.0140</td>
<td>0.0050</td>
<td>6.1000</td>
<td>1.1452</td>
<td>−0.9622</td>
<td>14.0191</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

3. Method

The nonlinear autoregressive neural network model is investigated here for price forecasting of carbon emission allowances traded in China Guangdong Carbon Emission Exchange. The model can be expressed as \( y_t = f(y_{t-1}, \ldots, y_{t-d}) \), where \( y \) is the price to be forecasted, \( t \) indexes time, \( d \) is the number of delays, and \( f \) represents the function. The current study concentrates on one-day ahead forecasts. And the model based upon a two-layer feedforward network is employed.

The final model is based on four delays and five hidden neurons. The Levenberg-Marquardt (LM) algorithm [164,165] is employed for estimating the model and the data are split following the ratio of 60% vs. 20% vs. 20% for training, validation, and testing.

Different algorithms can be considered for model training. Here, the scaled conjugate gradient (SCG) algorithm [166] is examined as well. The SCG and LM algorithms have been adopted widely in different fields [167–179]. Comparative research of these algorithms might be found from the literature [180–186].

The LM technique helps to avoid costly Hessian matrix computation by approximating the second-order training speed. The LM method avoids many of the drawbacks of Gauss-Newton techniques and steepest descent algorithms while still possessing many of their desirable features. In particular, it can effectively address the sluggish convergence issue.

Although the performance function will rapidly decline in that direction,
backpropagation algorithms alter weights in the steepest descent, which does not always correspond to the fastest convergence. The conjugate direction is searched via conjugate gradient algorithms, which often result in faster convergence than the steepest descent. The majority of algorithms use learning rates to calculate the updated weight step size. Iterations include changing the step sizes for conjugate gradient algorithms. In order to find the step size for lowering the performance function, the search is thus carried out in the conjugate gradient direction. Additionally, the SCG technique, which is faster than LM backpropagation and completely automated and supervised, might be utilized to circumvent the time-consuming line searches seen in conjugate gradient algorithms.

Finally, in arriving at our final model mentioned before, different model settings over delays, hidden neurons, and data spitting ratios, in addition to algorithms, are examined. Specifically, delays of two, three, four, five, and six, hidden neurons of two, three, five, and ten, and data spitting ratios of 60% vs. 20% vs. 20%, 70% vs. 15% vs. 15%, and 80% vs. 10% vs. 10% for training, validation, and testing are explored. 

Table 2 shows all investigated model settings, where the setting #65 is utilized to build our final chosen model.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>LM</th>
<th>SCG</th>
<th>Model Setting</th>
<th>k = 0,1, ..., 59</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delay</td>
<td>2</td>
<td>1 + 2k</td>
<td>1 + 10i–2 + 10i</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3 + 10i–4 + 10i</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>5 + 10i–6 + 10i</td>
<td>i = 0,1, ..., 11</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>7 + 10i–8 + 10i</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>9 + 10i–10 + 10i</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hidden</td>
<td>2</td>
<td>1 + 40j–10 + 40j</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neuron</td>
<td>3</td>
<td>11 + 40j–20 + 40j</td>
<td>j = 0,1,2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>21 + 40j–30 + 40j</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>31 + 40j–40 + 40j</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training vs. Validation vs. Testing Ratio</td>
<td>70% vs. 15% vs. 15%</td>
<td>1–40</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>60% vs. 20% vs. 20%</td>
<td>41–80</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>80% vs. 10% vs. 10%</td>
<td>81–120</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4. Result

All model settings listed in Table 2 are run for daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange. For a given model setting, the relative root mean square error (RRMSE) is calculated as the performance metric across training, validation, and testing phases, and the results are shown in Figure 2. The RRMSE is defined as follows:
\[ RRMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_{i, obs} - y_{i, for})^2} \]

where the equation \( y_{for} \) represents the target’s projected numerical value, \( y_{obs} \) represents the observed numerical value of the target variable, \( n \) denotes the number of observations utilized for performance assessments. Balancing model performance and stability, the setting #65 (four delays and five hidden neurons) is chosen, which is based on the LM algorithm and the data splitting ratio of 60% vs. 20% vs. 20% for training, validation, and testing.

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\[ MAE = \frac{1}{n} \sum_{i=1}^{n} |y_{i, obs} - y_{i, for}| \]

based on the setting #65 is 0.6635 for the training phase, 0.6377 for the validation phase, and 0.6614 for the testing phase. The overall MAE is 0.6579.

Figure 2. RRMSEs across all model settings for daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange.

With the chosen setting, sensitivities of performance to different settings are analyzed by changing one setting each time and the results are presented in Figure 3, where RRMSEs for training, validation, and testing based on each setting are shown. The comparison between the settings #65 and #66 tests the sensitivity to the algorithm, between the setting #65 and settings #61, #63, #67, and #69 the sensitivity to the delay, between the setting #65 and settings #45, #55, and #75 the sensitivity to the hidden neuron, and between the setting #65 and settings #25 and #105 the sensitivity to the data splitting ratio. These results support the setting #65 as the final choice, leading to RRMSEs of 4.59%, 4.69%, and 4.88% for the training, validation, and testing phases, respectively, and the overall RRMSE of 4.67%. Correspondingly, the mean absolute error (MAE) defined as

Overall, the chosen setting results in accurate and stable performance, suggesting usefulness of the neural network for forecasting daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange. One could also observe that forecast errors are relatively larger during periods with elevated price volatilities, such as those at the beginning of the training phase. This might not be surprising and the model generally still captures the trends during these periods.
Figure 3. Sensitivities of model performance (the RRMSE) to different model settings for daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange.

Figure 4. Forecasts (top) and forecast errors calculated as observations minus forecasts (bottom) for daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange.

We conduct benchmark analysis of our chosen neural network (NN) model against the support vector regression (SVR), random forest (RF), and autoregressive (AR) models. These three benchmark models use the same number of delays, which is four, as our chosen NN model. The RRMSEs based on the SVR, RF, and AR models are 9.36%, 10.09%, and 14.15%, respectively, for the testing phase, as compared to the RRMSE of 4.88% based on our chosen NN model, suggesting that the chosen NN model leads to higher accuracy. We also compare the chosen NN model with the three benchmark models based on the modified Diebold-Mariano test, which leads to p-values below 0.001, indicating that performance based on the chosen NN model is statistically significantly better than the three benchmark models.

5. Conclusion

Forecasting prices of carbon emission allowances is a significant issue for policy makers and investors [187,188]. In the present study, this forecasting problem is investigated in a dataset of daily closing prices of carbon emission allowances traded in China Guangdong Carbon Emission Exchange during 19 December 2013–20 August 2021. The nonlinear autoregressive neural network is considered as the forecasting tool and is explored over different model settings, leading to generally accurate and stable performance. In particular, the chosen model with four delays and five hidden neurons is constructed with the Levenberg-Marquardt algorithm [164,165] and a data splitting ratio of 60% vs. 20% vs. 20% for training, validation, and testing phases. It leads to relative root mean square errors (RRMSEs) of 4.59%, 4.69%, and 4.88% for the training, validation, and testing phases, respectively, and the overall
RRMSE of 4.67%. Results here might be used on a standalone basis as technical forecasts or combined with fundamental forecasts for forming perspectives of price trends and conducting policy analysis. The forecasting framework here should not be difficult to implement, which is an important consideration to many decision makers [35,189], and has potential to be generalized to related forecasting problems in different economic sectors, such as the energy, metal, mineral, and agriculture. One potential limitation of this work is that we focus on carbon emission allowance price forecasting for China Guangdong Carbon Emission Exchange, thus not covering other regions. Exploring carbon market data from other regions or prediction results of different market conditions should also represent a fruitful direction to pursue. Future research of interest might be investigating the potential of combining time series approaches and graph theory from machine learning for price forecasting [190–195]. Investigating economic significance of adopting neural network modeling for price forecasts might also be a worthwhile avenue for future research [196–198]. Another potential limitation of this work is that we focus on the nonlinear autoregressive neural network model for building forecasting models, thus taking into consideration the lagged price series as the predictive information sources. Future work could consider incorporating additional exogeneous variables into the model for potential accuracy improvements if more relevant data could be collected.

Author contributions: Conceptualization, BJ and XX; methodology, BJ and XX; software, BJ and XX; validation, BJ and XX; formal analysis, BJ and XX; investigation, BJ and XX; resources, BJ and XX; data curation, BJ and XX; writing—original draft preparation, BJ and XX; writing—review and editing, BJ and XX; visualization, BJ and XX; supervision, BJ and XX; project administration, BJ and XX. All authors have read and agreed to the published version of the manuscript.

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