

Carbon Price Prediction for the European Carbon Market Using Generative Adversarial Networks

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Abstract

Carbon price prediction is an important research interest. Deep learning has latterly realized triumph because of its mighty data processing competence. In this paper, a carbon price forecasting model of generative antagonistic network (GAN) with long short-term memory network (LSTM) as the generator and one-dimensional convolutional neural network (Conv1d) as the discriminator is proposed. The generator inputs historical carbon price data and generates future carbon prices, while the discriminator is designed to differentiate between the real carbon price and the generated carbon price. For verifying the validity of the proposed model, the daily trading price of the European carbon market is selected for numerical simulation, and compared with other prediction models, the GAN proposed has good property in carbon price prediction.

Keywords

Carbon Price Prediction, Generative Adversarial Network, Long Short-Term Memory Network, Convolutional Neural Network, Wasser-Stein Distance

1. Introduction

The high carbon dioxide emissions cause global warming, appearing extreme weather and serious environmental pollution problems. In 1997, the Kyoto Protocol (Lin, 2017) traded the emission rights of some greenhouse gases represented by carbon dioxide as commodities to form carbon emission rights trading. In the Paris Agreement, many countries have pledged to become carbon neutrality by 2050. Carbon emissions trading is the main way to achieve carbon neutrality, and this new trading model reduces carbon emissions through the independent

regulation of the market, which not only promotes economic progress but also has an effect on protecting environment. The European Union is the world's largest and most full-fledged carbon trading market (Zhou, Yang, & Shu, 2017). The carbon price is the kernel of carbon markets, and it has come into play in governments, enterprises and long-term investors. Therefore, accurate prediction of carbon price is a pivotal matter in the area of carbon market.

In recent years, generative adversarial networks (GAN) have solved the matter of sample shortage, and this model has been used to image processing (Zhang & Zhao, 2021), computer vision (Wang, She, & Ward, 2021), speech and natural language processing (Beguš, 2021), financial time series modeling (Takahashi, Chen, & Tanaka-Ishii, 2019), etc. GAN improves the accuracy of prediction through the game between generator and discriminator. In energy prediction (Bendaoud, Farah, & Ahmed, 2021), stock price prediction (Zhang, Zhong, Dong, Wang, & Wang, 2019) and traffic flow prediction (Zhang, Wu, Shen, Chen, Wang, Zhou et al., 2021) respect, many scholars have conducted some research using GAN, but it has not been used to the field of carbon price prediction.

In the light of the above analysis, the purpose of this paper is to use GAN to predict carbon prices, and verify whether the antagonism of generator and discriminator can help enhance the prediction accuracy of carbon price. It also includes a comparison between Support Vector Machine Regression (SVR), BP neural networks, Extreme Learning Machines (ELM), and LSTM with primitive GAN and Wasserstein GAN with Gradient Penalty (WGAN-GP) models. The main contributions of this article are as follows:

- This paper comes up with a carbon price prediction model (WGAN-GP) using GAN with LSTM as the generator and Conv1d as the discriminator, proving the antagonism between the generator and the discriminator of the GAN can enhance the precision of prediction of the carbon price.
- WGAN-GP which introduces Wasserstein distance and uses the gradient norm of the penalty discriminator replacing the Lipschitz constraint, successfully avoids the problems of GAN gradient disappearance, instability and model collapse, and enhances precision of prediction of carbon price.
- In the European carbon market, WGAN-GP is compared with SVR, BP, ELM, LSTM and the original GAN to highlight the high predictive accuracy.

2. Related Works

Traditional statistical and econometric models, such as ARIMA (Zhu, Chevallier, Zhu, & Chevallier, 2013) and GARCH (Byun & Cho, 2013), use historical data for linear regression, which has a good short-term prediction on carbon prices, but a large error in medium and long-term predictions. Although statistical models can availablely capture the fluctuations of carbon prices over time, the non-linear and non-stationary processing power of carbon price sequences is poor. Machine learning is an important means of non-linear data. The machine

learning model can extract non-linear features of the carbon price, such as BP (Sun & Huang, 2020), ELM (Sun & Zhang, 2018; Xu, Wang, Jiang, & Yang, 2020), LSTM (Huang, Dai, Wang, & Zhou, 2021). But such models often contain more arguments, resulting in over fitting. Considering that there are linear and non-linear features of the carbon price, combine traditional statistical models fitting linear features and machine learning models fitting non-linear features, such as GARCH-LSTM (Huang, Dai, Wang, & Zhou, 2021), ARIMA-SVM (Lu, Du, & Cao, 2020), ARIMA-CNN-LSTM (Ji, Zou, He, & Zhu, 2019). It indicates that the combination model has a preferable predictive effect. Traditional statistical and machine learning models have poor feature extraction ability on account of the non-stationary of carbon price sequences. Mode decomposition models can lessen the complexity and non-stationary of carbon price sequences, such as empirical mode decomposition (EMD) (Zhu, Han, Wang, Wu, Zhang & Wei, 2017), empirical wavelet transform (EWT) (Liu & Shen, 2020), Variational mode decomposition (VMD) (Chai, Zhang, & Zhang, 2021; Wang, Cheng, & Sun, 2022), complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) (Zhou, Huang, & Zhang, 2022; Zhao, Zhao, Li, Wu, & Guo, 2023; Yang, Wang, Zhao, Chen, & Li, 2023), which can effectively enhance the precision of prediction of the carbon price.

Some scholars have used GAN for time-series prediction. Zhang et al. (2019) proposed a stock price prediction model of GAN with multi-layer perceptron (MLP) as the discriminator and LSTM as the generator, indicating that compared with other prediction models, the proposed model has good property in stock price prediction. Zhang et al. (2021) proposed a mechanism on account of self-attention and GAN (SATP-GAN), consisting of a GAN module and a reinforcement learning (RL) module. In the GAN module, the self-attention layer is used to extract the features of the time-series data. In the RL module, the RL algorithm is applied to adjust the parameters of the SATP-GAN model. It shows that the self-attention layer replacing the RNN captures the input data features, which can be accelerated by parallel computing. Huang et al. (2022) proposed a stock price prediction model of GAN with gating cycle unit (GRU) as the generator and convolutional neural network (CNN) as the discriminator, indicating that the antagonism between the generator and the discriminator of GAN helps to enhance the precision of prediction of stock price.

3. Method

GAN have been utilized to predict time-series, and the parameters of the model are updated by means of the game between the generator and the discriminator, for the sake of enhancing the precision of prediction of the series. This section details the specific architecture of GAN, which is a carbon price prediction model using GAN with LSTM as the generator and Conv1d as the discriminator. First, the input of the generator of GAN model is formed from three-dimensional data of batch size, input-step and features, and the output is formed from three-

dimensional data of batch size, output-step and features. The batch sizes are all set to 64, and feature is all 1. The generator inputs the historical carbon price for the previous 5 days to generate the carbon price for the 6th day, that is, input-step is 5 and output-step is 1. The generator uses a layer of LSTM which the number of neurons is 128, and then adds a layer of Dense which the number of neurons is 1. Second, the discriminator included three Conv1d layers containing 32, 64 and 128 neurons, respectively, and finally added two layer of Dense including 256 and 1 neurons, respectively. In particular, in the discriminator, we combine the generated carbon price with the historical carbon price of the input-step as the input of the discriminator, because the discriminator can extract the pertinence and time-series message between the generated carbon price and the historical carbon price, which improves the accuracy of the discriminator's learning classification. Finally, the leaky rectified linear unit (ReLU) is regard as the activation function among all layers, while the original GAN output layer is the Sigmoid activation function and the output layer of WGAN-GP is the linear activation function. The output of the Sigmoid function is a scalar, 0 or 1, representing false or real data, while the output of linear function is a scalar score. The specific GAN architecture is as follows (Figure 1).

3.1. GAN

GAN is an unsupervised learning method for complex distributions. In general, a GAN is formed from two components, a generator (G) and a discriminator (D), which can be multifarious nonlinear mapping functions, for instance, machine learning models and deep neural networks. The purpose of the generator is to generate data that look as realistic as possible, and the goal of the discriminator is to differentiate real data or generate data. The discriminator outputs 0 when input generated data and 1 when real data is input. The basic idea of GAN is a minimax problem on account of zero-sum non-cooperative countermeasures (Lin, Chen, Huang, & Jafari, 2021). In the game competition, both the generator and the discriminator are constantly updated until the ideal point is reached that the discriminator cannot differentiate the two types of data, scilicet the data generated by the generator is similar to the primordial data, indicating that the GAN has completed the training. At this moment, the discriminator's output is 0.5. In the original GAN, the loss function is on account of the KL-JS divergence, and during training, the GAN model will utilize cross-entropy loss to minimize the discrepancy between the two distributions. The loss function of the discriminator is:

$$-\frac{1}{m} \sum_{i=1}^m \left[\log D(y^i) + \log(1 - D(G(x^i))) \right] \quad (1)$$

The loss function of the generator is:

$$-\frac{1}{m} \sum_{i=1}^m \log(D(G(x^i))) \quad (2)$$

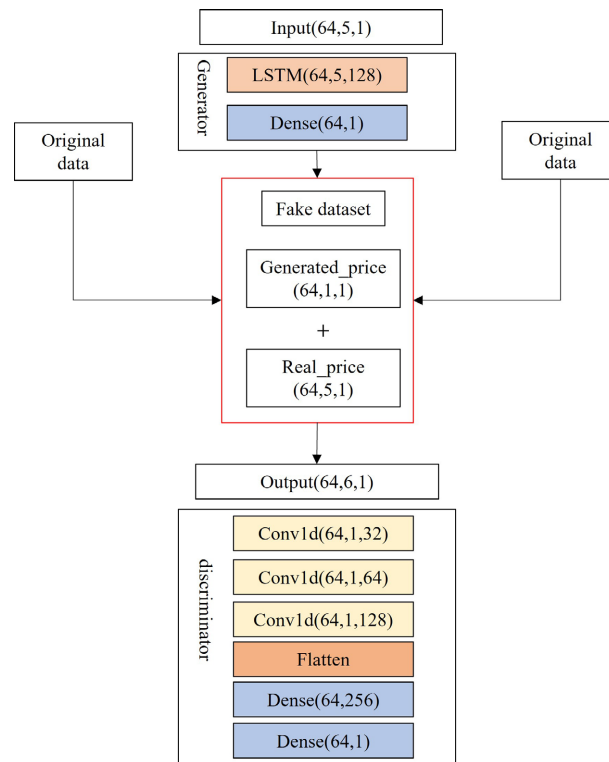


Figure 1. Architecture of GAN.

where x is the input of the generator, namely the historical carbon price, which y is the real carbon price, and $G(x^i)$ is the carbon price generated by the generator.

However, the GAN training process is slow and unstable, and often suffers from pattern crashes and discriminators winning matches (Yang, Wang, Zhao, Chen, & Li, 2023). Therefore, WGAN-GP, which introduces the Wasserstein distance and proposes the norm of the gradient that penalizes the discriminator as an alternative to the Lipschitz constraint, can provide a smoother gradient for the generator, thus successfully avoiding the problems of gradient vanishing, instability, and model collapse. In contrast to the primordial GAN, the WGAN-GP has no Sigmoid function and the output is a scalar score rather than a probability. The loss function of the discriminant for WGAN-GP is:

$$-\frac{1}{m} \sum_{i=1}^m \left[D(y^i) - D(G(x^i)) + \gamma E \left(\left\| \nabla_{y^i - x^i} \right\|_2 - 1 \right)^2 \right] \tag{3}$$

The loss function of the WGAN-GP generator is:

$$-\frac{1}{m} \sum_{i=1}^m D(G(x^i)) \tag{4}$$

3.2. LSTM

The LSTM network is a special recurrent neural network (RNN), which has been regarded as a powerful method for classification and prediction (Huang, Li, Tai, Chen, Liu, Shi, & Liu, 2022). Because of the issue of the long-range dependence

of the standard RNN, the LSTM uses the gating mechanism to control the cumulative speed of information. Add selectively new information and forget selectively previously accumulated information. The specific network structure is shown in **Figure 2**. LSTM introduces the input gate i_t , the forget gate f_t and the output gate o_t . x_t the actual carbon price at time t . The cell state c_t representing long-term memory is introduced to transmit linear circular information, which is outputted to the hidden layer h_t . It also introduces the candidate state \tilde{c}_t waiting to be stored into c_t . LSTM computation is given as follows:

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (5)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (6)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (7)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (8)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \quad (9)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (10)$$

where σ is the sigmoid activation function, W and U is weight, and b is deviation.

4. Experimental Test

For verifying the effectiveness of the WGAN-GP model, 5 models are chosen for contrast, including one machine learning model, two feed-forward neural networks, one recurrent neural network, and two GAN prediction models, namely SVR, BP, ELM, LSTM, GAN, and WGAN-GP.

4.1. Experimental Setting

The experimental environment is a window 10 operating system, the processor is Intel(R) Core (TM) i5-7200U CPU @ 2.50GHz, the storage is 1.0 TB, and the programming language of the prediction model is python 3.9. The parameter settings of prediction models are displayed in **Table 1**.

4.2. Evaluation Metrics

So as to testify the predictive capacity of the WGAN-GP model, three error evaluation metrics are chosen to assess the predictive accuracy of the model, including mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE). The specific expressions are as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (11)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (12)$$

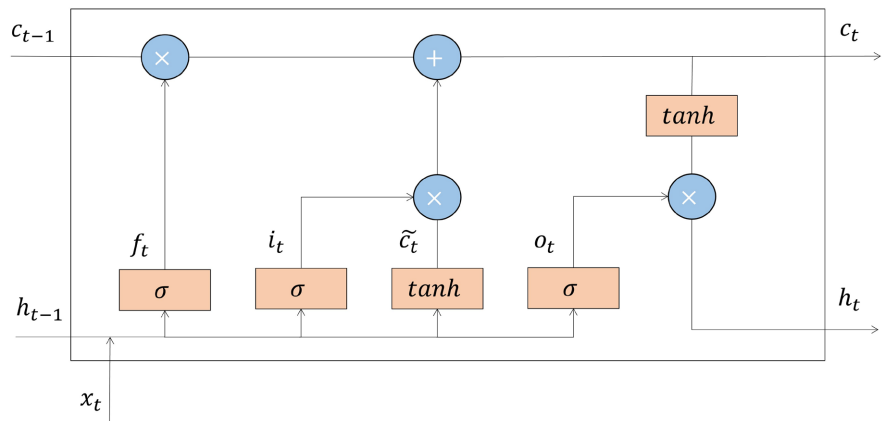


Figure 2. LSTM cell.

Table 1. Parameter settings of the model.

Model	Parameter settings
SVR	kernel = 'rbf', C = 100, gamma = 0.001
BP	string = {'logsig', 'purelin'}, func_str = 'trainlm', the number of neurons = [3, 2], learning rate = 0.001, epochs = 500
ELM	C = 10 (The inverse of the regular coefficient), the number of neurons = 5
LSTM	the number of neurons = 128, learning rate = 0.0001, batch_size = 64, epochs = 500
GAN	learning rate = 0.0001, batch_size = 64, epochs = 500
WGAN-GP	learning rate = 0.0001, batch_size = 64, epochs = 500

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right| * 100\% \tag{13}$$

MAE mirrors the global average deviation of the predicted value. RMAE reflects sample standard deviation between the predicted value and the true value, on behalf of the holistic dependability of the forecast. MAPE manifests the fitting effect of the forecasting model, which is a dimensionless error evaluation metrics. The smaller the three evaluation metrics, the more accurate the predictive results.

Meanwhile, percentage of root mean squared error (P_{RMSE}) is used to estimate the superiority between the model. The positive and negative of P_{RMSE} indicates the direction of performance improvement, the size of P_{RMSE} indicates the degree of model improvement. If P_{RMSE} is greater than 0, then model B is better than Model A. If P_{RMSE} is less than 0, then model A is better than Model B. The higher the positive value, the better the performance of model B than that of model A. The specific expression is as follows:

$$P_{RMSE} = \frac{RMSE_A - RMSE_B}{RMSE_A} * 100\% \tag{14}$$

where $RMSE_A$ represents $RMSE$ of model A and $RMSE_B$ represents $RMSE$ of

model *B*.

4.3. Experimental Data

The data are got from Wind database (<https://www.wind.com.cn/>). In this paper, the daily trading price of EU allowance (EUA) was selected from January 2, 2013 to December 30, 2022, with a total of 2581 samples for empirical analysis. **Figure 3** shows the daily trading price of EUA, from which it can be seen that the trading price of EUA is trending upward, with high uncertainty, non-linearity, dynamics and complexity. In this paper, the top 90% of the daily trading price of the EUA is used as the training set, and the bottom 10% is used as the test set, as shown in **Table 2**.

The descriptive statistics of carbon prices in the EU carbon market are shown in **Table 3**, the minimum value is 2.7, the maximum value is 97.58, and the average value is 22.95. The maximum value, minimum value and mean value of carbon price are consistent with **Figure 3**. Judging the degree of fluctuation from the coefficient of variation and standard deviation, the standard deviation of EUA is 24.66 and the coefficient of variation is 1.07, indicating the large degree of fluctuation of carbon price. As for the distribution pattern, according to the skewness and kurtosis, it can be seen that the trading price of EUA is right-biased, manifesting that the carbon trading price is significantly non-normal.

In addition, use the Augmented Dickey-Fuller (ADF) test and Brock-Dechert-Scheinkman (BDS) test to test the stationarity and non-linearity of the carbon price sequences, respectively. The results are revealed in **Table 4** and **Table 5**. In **Table 4**, all p-values greater than the critical value of 0.1. In other words, carbon price of the EU exist unit roots, illustrating that there is non-stationary features. In **Table 5**, all p-values are less than the critical value of 0.1, which means that the carbon price of EUA have the non-linear features.

4.4. Experimental Results and Analysis

In this paper, the WGAN-GP model is used to forecast the carbon price of the European carbon market, and compare and analyze it with the five models mentioned above to attest the validity of our proposed prediction model. Moreover, the results of the WGAN-GP and 5 prediction models are analyzed. The numerical results of RMSE, MAE and MAPE are presented to compare the predictive ability among different models, and also give the results of P_{RMSE} to compare the quality among different models.

The actual carbon prices for the European carbon market and the prediction results of each model are shown in **Figure 4**, and the prediction results of the WGAN-GP model are closer to its true price. **Table 6** shows the error analysis of the forecasting results of carbon prices by different models. To make the comparison clearer and more intuitive, **Figure 5** shows the RMSE and MAE radar plots of the SVR, BP, ELM, LSTM, GAN and WGAN-GP prediction models for the European carbon market. **Figure 6** shows the bar plot of the MAPE of the

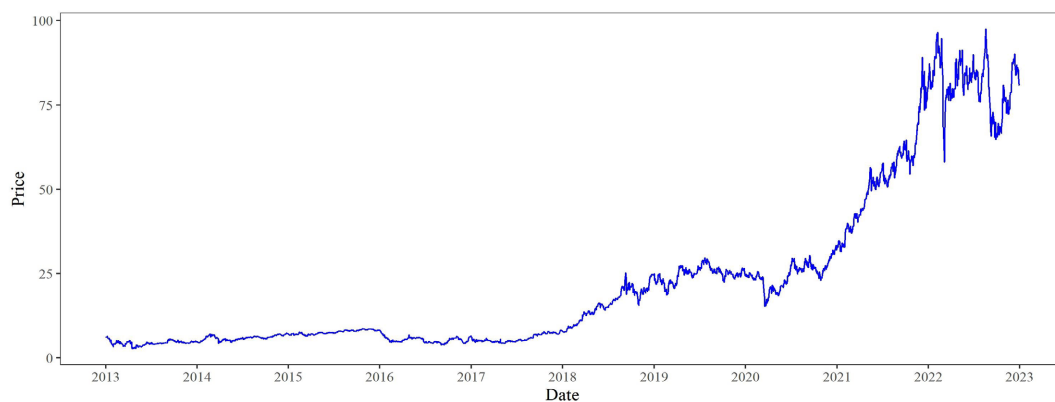


Figure 3. The EUA trading price.

Table 2. Basic information of the data.

	Data size	Date
Sample set	2581	2013-01-02—2022-12-30
Training set	2323	2013-01-02—2021-12-31
Testing set	258	2022-01-03—2022-12-30

Table 3. Descriptive statistics of carbon prices.

Statistics	Minimum	Maximum	Mean	Median	Std	CV	Skewness	Kurtosis
Value	2.70	97.58	22.95	8.58	24.66	1.07	1.48	1.02

Table 4. Results of the ADF tests.

Method	t-Statistic	P-value
Intercept	0.2710	0.9768
Intercept and trend	-1.6993	0.7516
None	1.2320	0.9449

Table 5. Results of the BDS tests.

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.2418	0.0021	112.8542	0.0000
3	0.3653	0.0025	144.7492	0.0000
4	0.4276	0.0022	191.5881	0.0000
5	0.4582	0.0017	264.9954	0.0000
6	0.4725	0.0012	380.8791	0.0000

Table 6. Error analysis of carbon price prediction of different model.

Evaluation indicators	Model					
	SVR	BP	ELM	LSTM	GAN	WGAN-GP
RMSE	5.091	4.612	3.922	3.682	3.360	3.040
MAE	4.205	3.928	3.143	2.751	2.500	2.208
MAPE	5.134%	4.457%	3.852%	3.472%	3.132%	2.776%

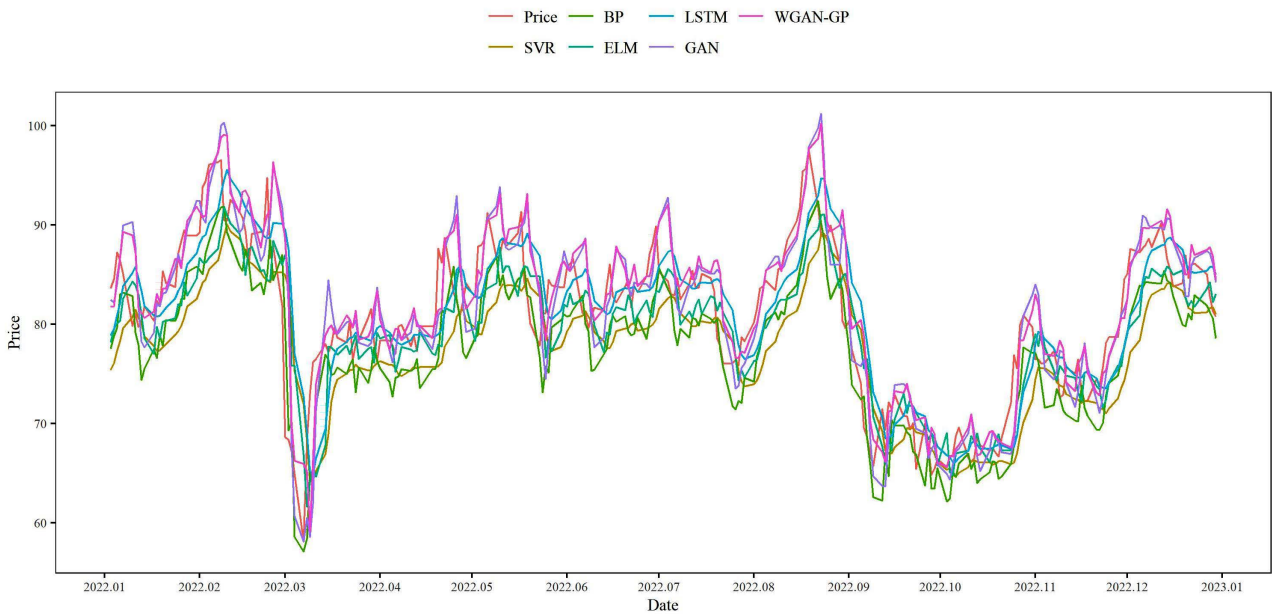


Figure 4. Prediction results of all models.

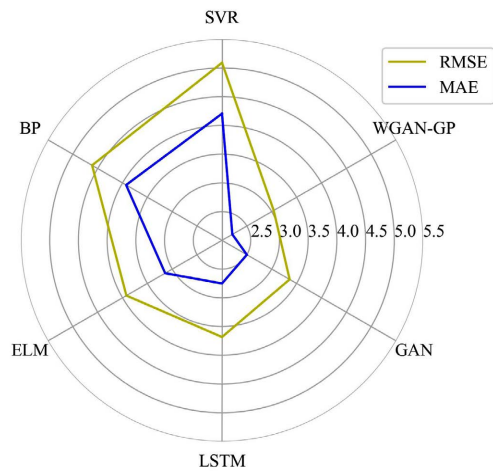


Figure 5. Radar chart of RMSE for all models.

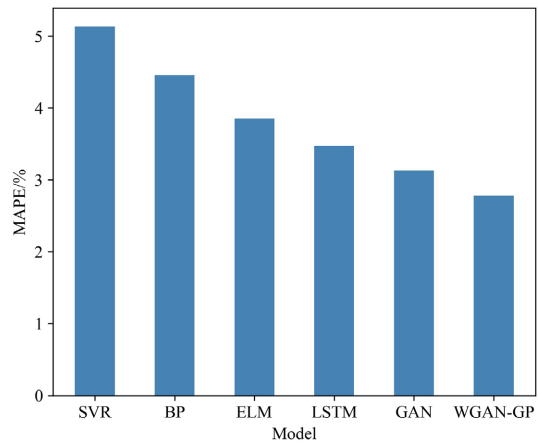


Figure 6. Bar chart of MAPE for all models.

prediction model for the European carbon market. **Table 7** shows the results of the P_{RMSE} among predictive models for the European carbon markets.

In **Table 6**, all indicators of the GAN with LSTM as the generator and Conv1d as the discriminator are smaller than all indicators of the LSTM, indicating that the antagonism between the generator and the discriminator of the GAN enhances the prediction accuracy of carbon price. In EU carbon markets, the RMSE, MAE and MAPE of the WGAN-GP model are 3.0405, 2.208 and 2.776% respectively. The RMSE, MAE and MAPE of the GAN model are 3.360, 2.500 and 3.132% respectively. The RMSE, MAE and MAPE of the LSTM model are 3.682, 2.751 and 3.472% respectively. In addition, all indicators of WGAN-GP are smaller than all indicators of the original GAN, indicating that WGAN-GP successfully avoids the problems of gradient vanishing, instability, and model collapse.

Figure 4 visually shows that the forecasting results of all model fluctuate with the actual carbon price. And the price predicted by the WGAN-GP model is closer to its true price. In **Figure 5**, the curve has the shape of a “snail shell”, and the results show that the RMSE and MAE of the prediction models gradually decrease counterclockwise from the SVR model. In **Figure 6**, the MAPE of the prediction models are reduced from left to right.

In **Table 7**, the GAN model has 8.74% higher prediction ability than LSTM model. At the same time, the prediction ability of WGAN-GP is 9.52% higher than that of the GAN model and is 17.43% higher than that of the LSTM model. The results show that the generator and discriminator in the GAN model which update the parameters by mutual game can enhance the precision of prediction of carbon price.

5. The Conclusions and Future Expectations

In this work, the paper comes up with a carbon price prediction model (WGAN-GP) using GAN with LSTM as the generator and Conv1d as the discriminator. Numerical experiments were carried out based on the carbon price of the European carbon market, and the error evaluation indexes of six models were compared: SVR, BP, ELM, LSTM, GAN and WGAN-GP.

The results reveal the prediction ability of the GAN is 8.74% better than that of the LSTM, indicating that the antagonism between the generator and the discriminator in GAN can enhance the prediction accuracy of carbon price. Moreover WGAN-GP has a 9.52% higher predictive power than GAN. The results show that WGAN-GP successfully avoids the problems of GAN gradient disappearance, instability and model collapse, and enhances precision of prediction of carbon price. It states clearly that compared with other models, the WGAN-GP model has the highest predictive accuracy. The predictive power of the LSTM model is 6.11% better than that of the ELM model and 20.16% better than that of the BP model. It illustrates that the deep neural network model has better predictive performance for carbon price than the simple feed-forward neural network model. The proposed model is important for predicting carbon price.

Table 7. Results of P_{RMSE} .

Model A \ Model B	BP	ELM	LSTM	GAN	
BP	9.40%				
ELM	22.96%	14.96%			
LSTM	27.67%	20.16%	6.11%		
GAN	34.00%	27.14%	14.32%	8.74%	
WGAN-GP	40.28%	34.08%	22.48%	17.43%	9.52%

In the future, a prediction model combining WGAN-GP with modal decomposition and multi-scale analysis can be constructed. Furthermore, this article does not focus on the impact of hyperparameters on the model. So attention should be paid to the tuning of the hyperparameters of each layer in the GAN model.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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