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A Novel Hybrid Price Prediction Model for Multimodal Carbon Emission Trading Market Based on CEEMDAN Algorithm and Window-Based XGBoost Approach

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Abstract: Accurate prediction of the carbon trading price (CTP) is crucial to the decision-making of relevant stakeholders, and can also provide a reference for policy makers. However, the time interval for the CTP is one day, resulting in a relatively small sample size of data available for predictions. When dealing with small sample data, deep learning algorithms can trade only a small improvement in prediction accuracy at the expense of efficiency and computing time. In contrast, fine-grained configurations of traditional model inputs and parameters often perform no less well than deep learning algorithms. In this context, this paper proposes a novel hybrid CTP prediction model based on the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and a windowed-based XGBoost approach. First, the initial CTP data is decomposed into multiple subsequences with relatively low volatility and randomness based on the CEEMDAN algorithm. Then, the decomposed carbon valence series and covariates are subject to windowed processing to become the inputs of the XGBoost model. Finally, the universality of the proposed model is verified through case studies of four carbon emission trading markets with different modal characteristics, and the superiority of the proposed model is verified by comparing with seven other models. The results show that the prediction error of the proposed XGBoost(W-b) algorithm is reduced by 4.72%~81.47% compared to other prediction algorithms. In addition, the introduction of CEEMDAN further reduces the prediction error by 25.24%~89.28% on the basis of XGBoost(W-b).

Keywords: carbon trading price forecasting; complete ensemble empirical mode decomposition with adaptive noise; windowed-based XGBoost; multimodal carbon emission trading market

MSC: 91B84; 62M10

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Citation: Zhang, C.; Zhao, Y.; Zhao, H. A Novel Hybrid Price Prediction Model for Multimodal Carbon Emission Trading Market Based on CEEMDAN Algorithm and Window-Based XGBoost Approach. *Mathematics* **2022**, *10*, 4072. https://doi.org/10.3390/math10214072

Academic Editor: António Lopes

Received: 9 October 2022
Accepted: 29 October 2022
Published: 1 November 2022

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1. Introduction

1.1. Background and Motivation

In order to solve the climate change problem, a series of carbon emission reduction policies have been launched in recent years [1]. Of which, the establishment of the carbon market is considered to be one of the most effective emission-reduction policy tools, due to its characteristics of low cost and sustainability [2,3]. According to the International Carbon Action Partnership, as of 31 January 2021, there were 24 carbon markets in operation around the world, with another eight carbon markets under planning and 14 jurisdictions considering the establishment of carbon markets (International Carbon Action Partnership (https://icapcarbonaction.com/en (accessed on 1 October 2022))). The carbon trading price (CTP) is the core element of the carbon emission trading (CET) market. Accurate CTP prediction will help the government to formulate carbon market policies scientifically, which will also help enterprises make effective decisions and minimize the cost of carbon emission reduction [4]. However, the trends and fluctuations in CTP vary from region to region due to significant differences in resource endowments and market development

stages. Therefore, it is necessary to propose a more universal CTP prediction model to adapt to the characteristics of multimodal CET markets while also taking into account efficiency issues.

1.2. Literature Review

Similarly, CTP prediction is also a hot spot of scholars' attention in recent years. Table 1 lists the recent papers on CTP prediction and elaborates the models and contributions of these papers.

Table 1. The recent papers on CTP prediction.

Reference	Decomposition Model	Forecast Model	Application Scenario	Main Contribution and Novelty
Qin et al. [5]	HP filter and CEEMDAN	ARIMA and KELM	EU ETS and Hubei carbon market	The study contained data preprocessing, parameter optimization, component predictor and postprocessing.
Ji et al. [6]	/	ARIMA, CNN and LSTM	EU ETS	The study combined the statistical model and deep learning models.
Liu and Huang [7]	/	GARCH and FBM	EU ETS	The proposed model was more in line with the characteristics of carbon option prices.
Zhu and Wei [8]	/	ARIMA and LSSVM	EU ETS	The study established a novel hybrid carbon price forecasting model.
Wan et al. [9]	CEEMDAN	LSTM	Tianjin and Guangdong carbon markets	The research proposed an adaptive nonlinear ensemble learning paradigm.
Zhao et al. [10]	HP filter	VGM and ELM	EU ETS	The study observed the cross interaction between the carbon market and others.
Zhou et al. [11]	VMD and CEEMDAN	LSTM	Guangdong carbon market	The study made up for shortcomings of difficult to reproduce programming.
Wang et al. [12]	DWT, EMD, VMD and SSA	LSTM	Hubei carbon market	The study proposed a carbon price combination forecasting framework based on multi-source information fusion.
Yang et al. [13]	MEEMD	LSTM	Beijing, Fujian and Shanghai carbon market	The proposed model achieved higher prediction accuracy than 11 other models.
Zhu et al. [14]	EMD	GARCH and LSSVM	EU ETS	The research developed a novel multiscale nonlinear ensemble leaning paradigm.
Qi et al. [15]	EEMD	BP and ELM	China's national carbon market	The national carbon market price was used to reflect the social cost of carbon in China.

Summarizing the previous studies, the following conclusions can be obtained:

(1) In terms of the decomposition method, multiple decomposition models are applied for CTP prediction. Of which, HP filter can divide time series into cyclical fluctuation data and trend element data, but also introduces spurious dynamic relationships that are unrelated to the underlying data generation process [16]. Empirical mode decomposition method (EMD) is widely used for decomposing nonlinear and nonstationary time series, but will produce the modal aliasing phenomenon. Although the ensemble empirical mode decomposition method (EEMD) can effectively reduce the occurrence of mode mixing, it also introduces new challenges. The white Gaussian noise (WGN) added to the EEMD must be averaged repeatedly, and the error is primarily determined by the number of integrations [17]. Compared with the traditional EMD and EEMD algorithms, the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) algorithm can overcome the aforementioned problem by

adding a finite number of times of adaptive WGN at each period [18], which is also used in this paper.

(2) In terms of the prediction model, statistical models and machine learning models are widely used in CTP forecasting problems. With the continuous innovation of artificial intelligence technology and the development of the carbon market, some scholars try to introduce deep learning algorithms into CTP forecasting. In addition to the carbon market, more and more scholars use deep learning algorithms for price forecasting in the electricity market [19], energy market [20,21], stock market [22] and some other fields. It seems that deep learning algorithms can eliminate or replace some statistical models and machine learning models in price forecasting. However, some other scholars have raised objections. Shah and Shroff [23] found that the traditional ARIMA model performs much better than the deep learning algorithms such as LSTM and Transformer. Elsayed et al. [24] proposed an improved gradient boosting regression tree model, and the performance of the model was proven better than those of eight deep learning prediction algorithms proposed at nine top computer conferences, such as NeurIPS, from 2016 to 2020.

In fact, the time scale of the CTP is mainly daily, the step size of the current CTP forecast is also one day in most research (predicting the daily transaction price, daily average price, daily minimum price and daily maximum price). The superiority of deep learning algorithms often needs to be reflected in large-capacity and high-volatility sample data. When the sample size is small, the prediction accuracy improvement brought by the deep learning algorithm is not obvious, and it is easy to significantly increase the computation time. On the contrary, by carefully configuring the parameters and inputs of traditional models, the prediction accuracy and computational efficiency are often no less than deep learning algorithms.

(3) In terms of the application scenarios, most studies focus on CTP forecasting for the EU ETS market, while some studies are conducted for a few Chinese carbon pilots. Although the models proposed in these studies have good prediction accuracy and forecasting performance, the generalizability of the models is difficult to verify due to the small number of cases.

1.3. Contributions and Article Organization

Based on the previous research, this paper proposes a novel hybrid CTP forecasting model suitable for multimodal CET markets. First, the initial CTP data is decomposed using the CEEMDAN approach to decrease the volatility. Then, the window-based XGBoost model is applied to forecast the processed CTP data. Finally, four carbon markets with different characteristics are selected to be the case study. This study's main contributions and innovations are as follows:

(1) The CEEMDAN algorithm can help decompose the initial CTP data into multiple sequences with less volatility and less randomness, which can also help to improve the prediction accuracy. In addition, it can solve the modal aliasing problem and achieve better processing performance.

(2) By windowing the traditional XGBoost model, the multi-dimensional input variables are converted into a one-dimensional reconstruction vector, which not only reduces the complexity of the model, but also helps the model to capture the autocorrelation effect of the predicted object.

(3) Different carbon markets present different trading laws and price characteristics, and the analysis of multimodal carbon markets can better verify the universality of the proposed model. In this paper, the simulation analysis is carried out with the actual data of four carbon markets with different sample characteristics, and the superiority and feasibility of the model proposed in this paper are verified by comparing with several state-of-the-art methods.

The remaining sections of this research are organized as follows. Following the introductory section, Section 2 elaborates on the basic methodology used in this research. The model construction for CTP forecasting is introduced in Section 3. Section 4 contains the empirical analysis and discussion. The conclusions are obtained in Section 5.

2. Methodology

2.1. CEEMDAN Model

In 2011, Torres et al. [25] proposed the CEEMDAN algorithm with better processing performance on reducing data volatility, which also applies to solve the CTP prediction problem in this paper. The steps of CEEMDAN on CTP data are listed as follows:

➢ Step 1: Add a series of adaptive WGN to the initial CTP price x.

$$x^i(t) = x(t) + \omega_0 \varepsilon^i(t), i \in \{1, \cdots, I\} \tag{1}$$

where ω_0 represents the noise coefficient, $\varepsilon^i(t)$ represents the i-th addition of WGN at time t, $x^i(t)$ represents the processing CTP sequence after adding WGN at time t and I represents the integration number.

➢ Step 2: Decompose $x^i(t)$ using the EMD method and take the mean value of the first IMF component c_1^i.

$$c_1(t) = \frac{1}{I}\sum_{i=1}^{I} c_1^i \tag{2}$$

Remove $c_1(t)$ from the original CTP sequence to get the first residual sequence.

$$r_1(t) = x(t) - c_1(t) \tag{3}$$

➢ Step 3: Repeat Step 2 on $r_1(t) + \omega_1 E_1[\varepsilon^i(t)]$ to get the second residual sequence.

$$c_2(t) = \frac{1}{I}\sum_{i=1}^{I} E_1\left\{r_1(t) + \omega_1 E_1[\varepsilon^i(t)]\right\} \tag{4}$$

where $E_j(\cdot)$ represents the j-th IMF component decomposed using the EMD algorithm.

➢ Step 4: Calculate the remaining IMF components and repeat it as follows:

$$r_k(t) = r_{k-1}(t) - c_k(t), k = 2, 3, \cdots, K \tag{5}$$

$$c_{k+1}(t) = \frac{1}{I}\sum_{i=1}^{I} E_1\left\{r_k(t) + \omega_k E_k[\varepsilon^i(t)]\right\} \tag{6}$$

where K represents the total number of modes.

The loop will be ended until the residual series cannot be decomposed further, and the last residual can be expressed as:

$$R(t) = x(t) - \sum_{k=1}^{K} c_k(t) \tag{7}$$

2.2. Window-Based XGBoost Model

The basic principle of a gradient boosting decision tree (GBDT) is to iterate multiple regression trees to make joint decisions, thus achieving regression prediction of the target [26]. However, the traditional GBDT suffers from a series of problems such as easy overfitting and inability to parallelize computation. In 2016, Chen and Guestrin proposed an improved extreme gradient boosting (XGBoost) algorithm, which can overcome the above problems by optimizing the loss function, simplifying the model with regularization parameters, and using Blocks storage structure [27]. However, the XGBoost model is still

a tree model in essence, so it is better at analyzing the characteristics of some structured data. When dealing with time series problem such as CTP prediction, the flexibility and predictive accuracy will be greatly reduced.

In this paper, we further propose a window-based XGBoost model XGBoost(W-b) on the basis of the traditional XGBoost algorithm, which can reconfigure the CTP data as windowed inputs, as shown in Formula (8):

$$\mathbb{R}^{W\times(L+M)} \rightarrow \mathbb{R}^{(W+M)} \tag{8}$$

where W represents the window size, L represents the target channel and M represents the number of covariates (which can be also regarded as the influencing factors of CTP). In this paper, we only forecast the daily average transaction carbon price, so $L = 1$. Through the above conversion function, the two-dimensional time series can be converted into a one-dimensional vector. The basic principle of the XGBoost(W-b) algorithm is shown in Figure 1.

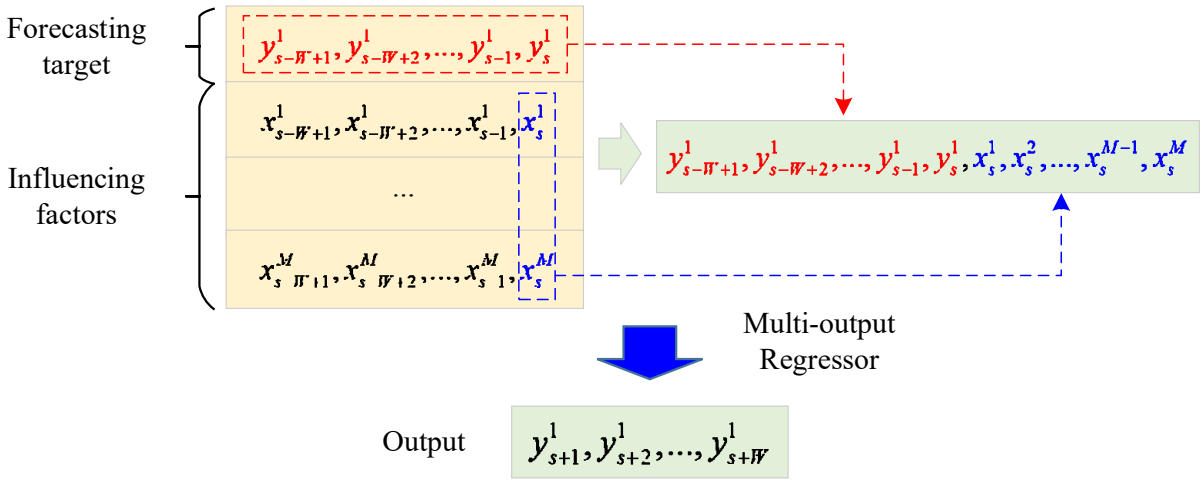


Figure 1. The basic principle of XGBoost(W-b) algorithm.

Through the XGBoost(W-b) algorithm, the complex multi-input forecasting problem can be converted into a simple regression problem, which can significantly simplify the spatial network structure of the prediction model, so as to shorten the computing time. In addition, through the windowed processing, the multi-step prediction of future CTPs can be easily achieved, which cannot only help to capture the autocorrelation effect in the target variable but also makes up for the defect of multi-output independent prediction [28].

3. Model Construction and Data Preprocessing for CTP Forecasting

3.1. Construction of the CTP Forecasting Model

The steps of CTP forecasting are listed as follows:

- Step 1: Based on the previous research, the key factors affecting the CTP are selected to be the covariate factors. Then, the raw CTP data and covariate factors are normalized.
- Step 2: The initial CTP data is decomposed into multiple series using the CEEMDAN method. Then, each intrinsic mode function (IMF) and the covariate factors are converted into a one-dimensional reconstruction vector using the XGBoost(W-b) model.
- Step 3: Each series component is predicted separately and the results are summed up to produce the final CTP prediction result. Four typical CET markets are used for this case study.
- Step 4: Comparison of model prediction accuracy from two dimensions: comparison between prediction methods XGBoost(W-b) and other machine learning and deep learning algorithms), and comparison between decomposition algorithms (CEEMDAN-XGBoost(W-b) and XGBoost(W-b) decomposed by other algorithms).

The framework of the CTP forecasting based on CEEMDAN and XGBoost(W-b) is shown in Figure 2 as follows:

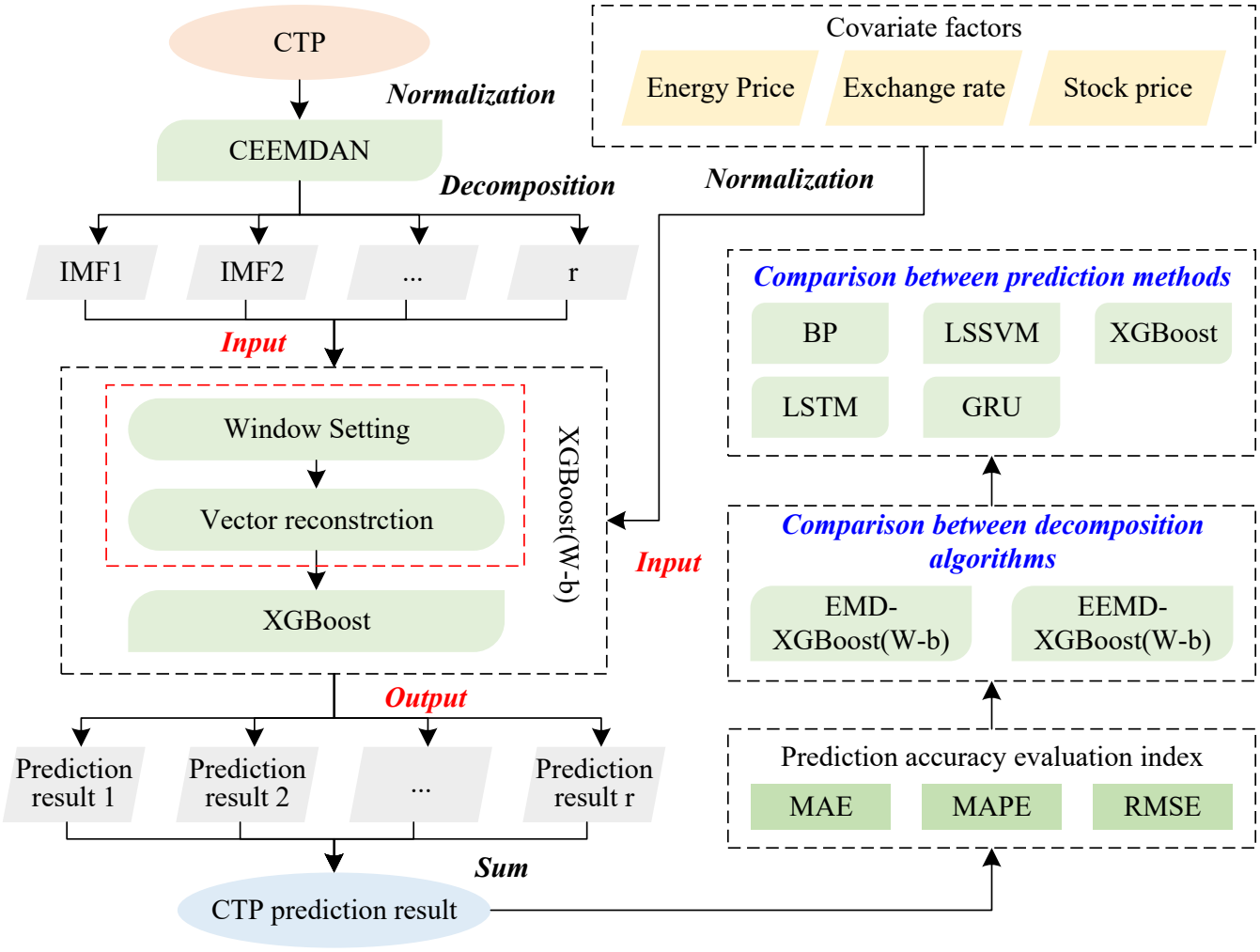


Figure 2. The framework of the CTP forecasting based on CEEMDAN and XGBoost(W-b).

3.2. Data Normalization

In this paper, the MinMax normalization model is applied to process the initial data, which can help speed up the computation [29].

$$x_i^* = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

where x_i^* represents the normalized data, $x_{\min}$ represents the minimum value of the data and $x_{\max}$ represents the maximum value of the data.

3.3. Prediction Accuracy Evaluation Index Selection

In order to better clarify the performance of the proposed model in CTP prediction, mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) are selected as the prediction accuracy evaluation index, respectively.

$$\varepsilon_{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{10}$$

$$\varepsilon_{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \times 100\% \tag{11}$$

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

4. Case Study

4.1. Data Description and Parameter Setting

In order to verify the superiority of the CTP prediction algorithm proposed in this paper, four carbon markets with different characteristics were selected as the study samples (China's national CET market, Fujian CET market, Hubei CET market and European Union emissions trading system).

(1) EU ETS

As the world's largest carbon market, the EU ETS was established on 1 January 2005 and has been in development for seventeen years. As one of the EU's main instruments for achieving emission reductions, EU ETS covers about 45% of EU carbon emissions, covering a wide range of sectors such as power, manufacturing and aviation. Over the years, EU ETS has gone through three stages of development (2005~2007, 2008~2012 and 2013~2020) and is currently in its fourth stage of development (2021~2030). After years of exploration, the scope of enterprises and the quota allocation mechanism have all been adjusted to varying degrees, resulting in significant price fluctuations in EU ETS.

(2) Hubei CET market

Different from EU ETS, China's CET market started relatively late. As one of the first carbon pilots to be launched, the Hubei CET market officially started trading in April 2014. As of July 2021, the participants in the Hubei CET market mainly include 373 emission control enterprises, 375 investment institutions and 10,389 users. The Hubei CET market covers 273 million tons of carbon emissions, accounting for about 45% of Hubei's carbon emissions. Among the first carbon pilots established in China, the Hubei CET market accounts for half of China's emissions trading volume and emissions trading value, and is one of the most active carbon pilots in China.

(3) Fujian CET market

Unlike other Chinese carbon pilots, the Fujian CET market, the eighth carbon pilot established in China, officially began trading at the end of 2016. As of 2020, the total annual quota issued by the Fujian carbon market has exceeded 200 million tons, ranking third in all the pilot provinces. The annual carbon market turnover has increased from 4,282,900 tons and RMB 113 million in the first compliance year to 6,974,200 tons and RMB 209 million in 2020. The compliance rate has remained 100% for four compliance cycles. The cumulative turnover of the Fujian carbon market has reached 27,496,700 tons and RMB 782 million. Despite its late start, the Fujian CET market has wide coverage and a full range of traded products, and the fluctuation of market prices is relatively obvious.

(4) China's national CET market

The construction of the national unified market can help fully play the decisive role of the market in the allocation of resources. It is of significance in reducing market transaction costs and promoting efficient market access. After eight pilot stages of exploration, China's national CET market also officially started trading on 16 July 2021. So far, it has already passed the first compliance cycle. Due to the characteristics of large emissions and a sound management system, the power generation industry was the first industry to be included in China's national CET market, resulting in a smaller floating carbon price change.

In addition to the CTP itself, the selection of influencing factors is also a key element affecting the CTP forecast. The frequently considered covariates mainly contain: energy market price [30–32], exchange rate [33], stock market price [34], green finance [35] and renewable energy [36]. Considering the data integrity and accessibility, five indicators are considered to be covariate factors for CTP prediction in this paper: WTI crude oil price, gas price, coal price, exchange rate between EUR and CNY and CSI 300 index. In addition, the

invalid data of CTP and covariate factors were excluded. The descriptive statistics of the data for prediction are listed in Table 2.

Table 2. The descriptive statistics of the data.

Carbon Emission Trading Market	Variables (Including Covariate)	Observation	Average	Min	Max	Std.
China's national CET market	CTP (CNY/tCO_2)	209 (16 July 2021–30 May 2022)	51.91	41.46	61.38	6.82
	WTI crude oil price ($/Barrel)		85.93	62.06	126.47	15.82
	Gas Price ($/mmbtu)		5.09	3.56	8.97	1.31
	Coal Price (CNY/tons)		984.44	608.00	2301.60	280.22
	EUR_CNY exchange rate		7.29	6.86	7.69	0.24
	CSI 300 index		4645.70	3794.60	5127.40	364.08
Fujian CET market	CTP (CNY/tCO_2)	851 (9 January 2017–19 August 2020)	20.91	7.19	42.28	8.80
	WTI crude oil price ($/Barrel)		54.49	10.01	76.41	12.05
	Gas Price ($/mmbtu)		2.62	1.48	4.84	0.56
	Coal Price (CNY/tons)		1300.64	963.00	1677.00	97.55
	EUR_CNY exchange rate		7.80	7.41	8.30	0.15
	CSI 300 index		3903.46	2959.20	5278.60	468.85
Hubei CET market	CTP (CNY/tCO_2)	1700 (2014.4.2–2020.9.15)	23.39	10.07	53.85	6.24
	WTI crude oil price ($/Barrel)		55.80	10.01	107.26	16.97
	Gas Price ($/mmbtu)		2.82	1.48	4.84	0.68
	Coal Price (CNY/tons)		1102.61	550.00	1835.50	330.50
	EUR_CNY exchange rate		7.61	6.57	8.68	0.40
	CSI 300 index		3633.36	2099.40	5801.20	699.65
EU ETS	CTP (€/tCO_2)	1870 (25 March 2013–24 February 2022)	18.62	2.75	97.51	18.71
	WTI crude oil price ($/Barrel)		62.81	10.01	110.53	21.54
	Gas Price ($/mmbtu)		3.04	1.55	6.15	0.76
	Coal Price (CNY/tons)		1251.07	550.00	3995.00	576.20
	EUR_CNY exchange rate		7.68	6.57	8.68	0.43
	CSI 300 index		3400.10	2071.00	5346.00	711.18

The computer used in the empirical analysis is an i7-1185G7 processor with 32 GB memory, and the simulation platform is Python 3.10.2. In order to verify the advancement of the CEEMDAN-XGBoost(W-b) algorithm proposed in this paper, seven models are selected from the dimensions of prediction and decomposition: BP, LSSVM, XGBoost, LSTM, GRU, XGBoost(W-b) and EEMD-XGBoost(W-b). The parameters of the models are set according to the relevant literatures, as listed in Table 3, and other parameters not listed in Table 3 are based on the model default values.

The data for prediction are divided into sample set, validation set and prediction set according to the ratio of 60%, 20% and 20%.

4.2. Comparison of Model Prediction Accuracy for Multiple Prediction Methods

In this part, the prediction results and accuracy of the models in different CET markets are shown in Figure 3 and Table 4.

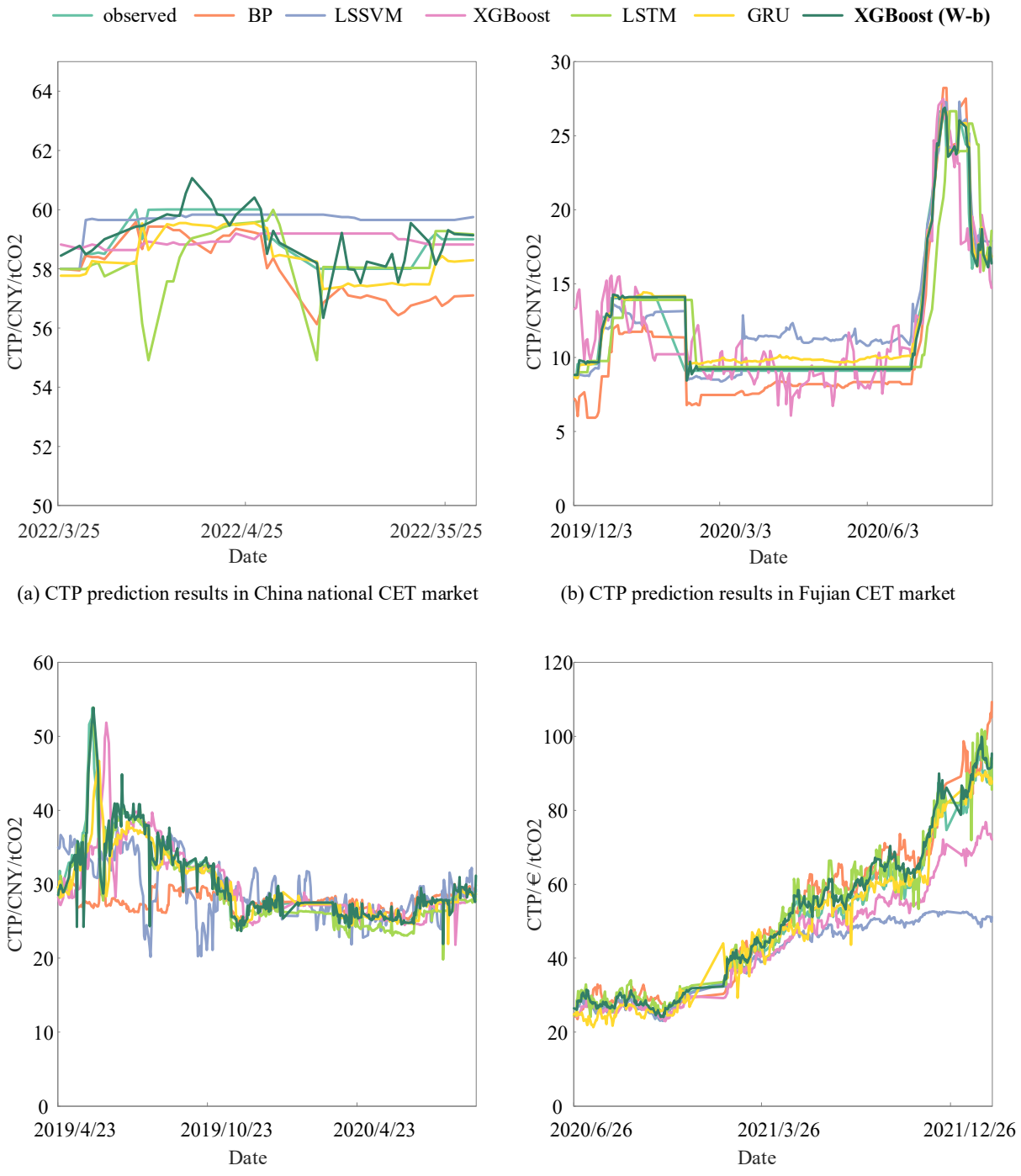
Table 3. Parameter setting of the models.

Model	Parameter	Value
BP [37]	hidden neurons	10
	epoch	300
LSSVM [38]	gam	[1, 1000]
	sig2	[0.01, 1]
LSTM [39]	epoch	300
	batch size	32
GRU [40]	epoch	300
	batch size	32
XGBoost and XGBoost(W-b) [19]	window size	1
	learning rate	0.025
	gamma	0
	max depth	2
	n estimators	300
	min child weight	1
	subsample	0.9
	colsample bytree	0.9
	scale pos weight	0.8
	seed	27
EEMD and CEEMDAN [41]	standard deviation	0.2
	white noise	500
	max iteration	1000

Table 4. The error of the forecasting models.

China's National CET Market	**MAE**	**MAPE**	**RMSE**
BP	0.98	1.67%	1.16
LSSVM	0.84	1.44%	1.05
XGBoost	0.80	1.35%	0.90
LSTM	0.76	1.28%	1.29
GRU	0.59	1.00%	0.67
XGBoost (W-b)	**0.41**	**0.70%**	**0.56**
Fujian CET market	**MAE**	**MAPE**	**RMSE**
BP	1.63	14.45%	1.89
LSSVM	1.50	14.40%	1.77
XGBoost	1.42	12.09%	1.93
LSTM	1.06	8.60%	2.45
GRU	0.69	6.30%	0.95
XGBoost (W-b)	**0.37**	**2.68%**	**0.75**
Hubei CET market	**MAE**	**MAPE**	**RMSE**
BP	3.40	9.41%	5.85
LSSVM	3.14	9.59%	4.68
XGBoost	2.18	6.59%	3.75
LSTM	1.30	4.42%	**1.62**
GRU	1.50	4.48%	2.84
XGBoost (W-b)	**1.01**	**3.14%**	1.84
EU ETS	**MAE**	**MAPE**	**RMSE**
BP	4.49	9.39%	5.83
LSSVM	8.12	11.80%	13.63
XGBoost	4.77	8.19%	6.89
LSTM	3.12	6.70%	3.82
GRU	**2.39**	5.53%	3.17
XGBoost (W-b)	2.60	**5.27%**	**3.16**

Note: Bold numbers present that the model has the lowest prediction error.



(a) CTP prediction results in China national CET market

(b) CTP prediction results in Fujian CET market

(c) CTP prediction results in Hubei CET market

(d) CTP prediction results in EU ETS

Figure 3. CTP prediction results for different forecasting methods.

As shown above, the prediction performance of each prediction model is different in multimodal CET markets. For China's national CET market, with a small sample size and data fluctuation, the prediction error of each model does not exceed 2% from the perspective of MAPE. The precision ranking of each prediction model is XGBoost(W-b) > GRU > LSTM > XGBoost > LSSVM > BP. When the data volatility is significantly improved (Fujian CET market), the prediction accuracy of each model shows a significant downward trend. However, the precision ranking of each prediction model does not change. For the Hubei CET market, with a relatively large sample size and small data fluctuation, the prediction error ranges between 3.14~9.59%. Different from the previous two markets, due to the

expansion of sample size, the performance of the LSSVM model is slightly worse than that of BP, and the prediction accuracy of the LSTM model is also slightly higher than that of GRU. When the sample size and data complexity increase synchronously, the MAPE of even the XGBoost (W-b) algorithm with the best forecasting performance reaches 5.27%. Under this situation, the performance of LSSVM is further deteriorated, and the precision ranking of each prediction model is XGBoost(W-b) > GRU > LSTM > XGBoost > BP > LSSVM. Compared to other algorithms, the decrease in prediction error of XGBoost(W-b) is shown in Table 5.

Table 5. The decrease in prediction error of XGBoost(W-b) compared to other algorithms.

CET Market	Prediction Error Decrease Proportion (%)
China's national CET market	30.69~58.34
Fujian CET market	57.49~81.47
Hubei CET market	28.92~67.21
EU ETS	4.72~55.35

4.3. Comparison of Model Prediction Accuracy for Multiple Decomposition Methods

In order to reduce the impact of data fluctuation on CTP prediction, the CEEMDAN algorithm is introduced in this paper, and the decomposition result of the initial CTP for China's national CET market (as an example) is shown in Figure 4.

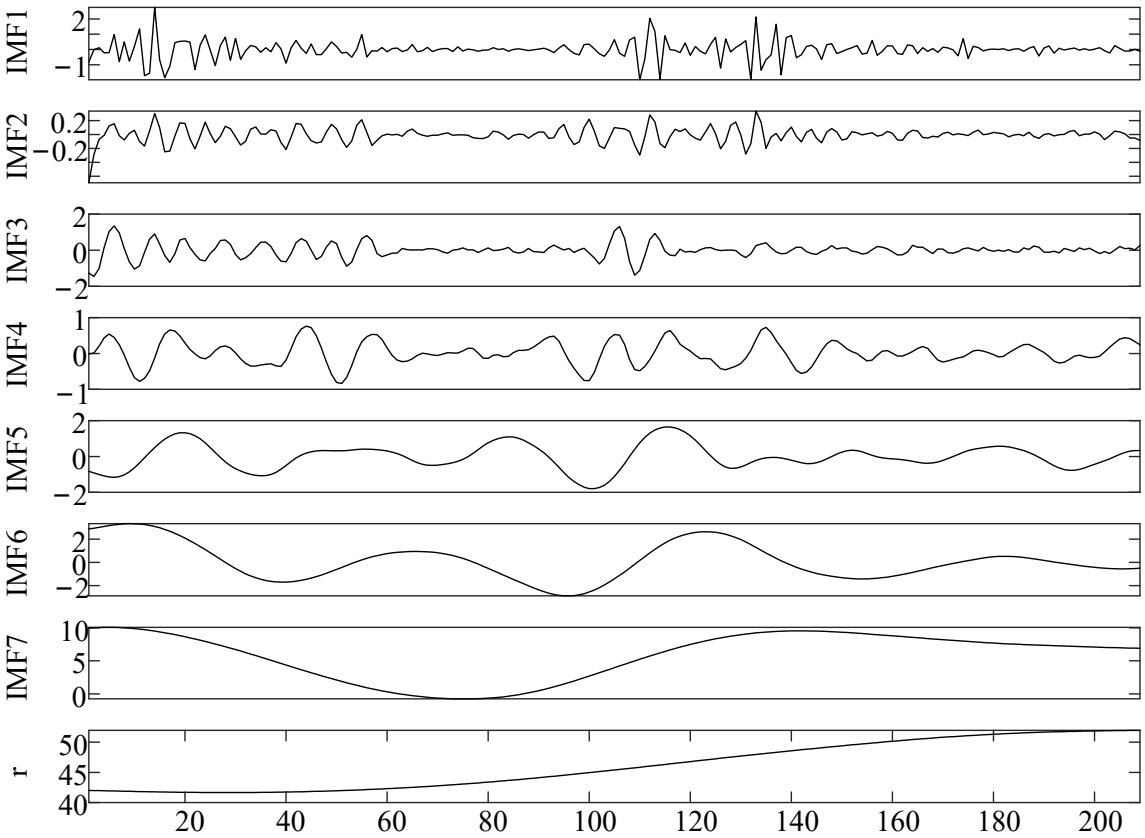
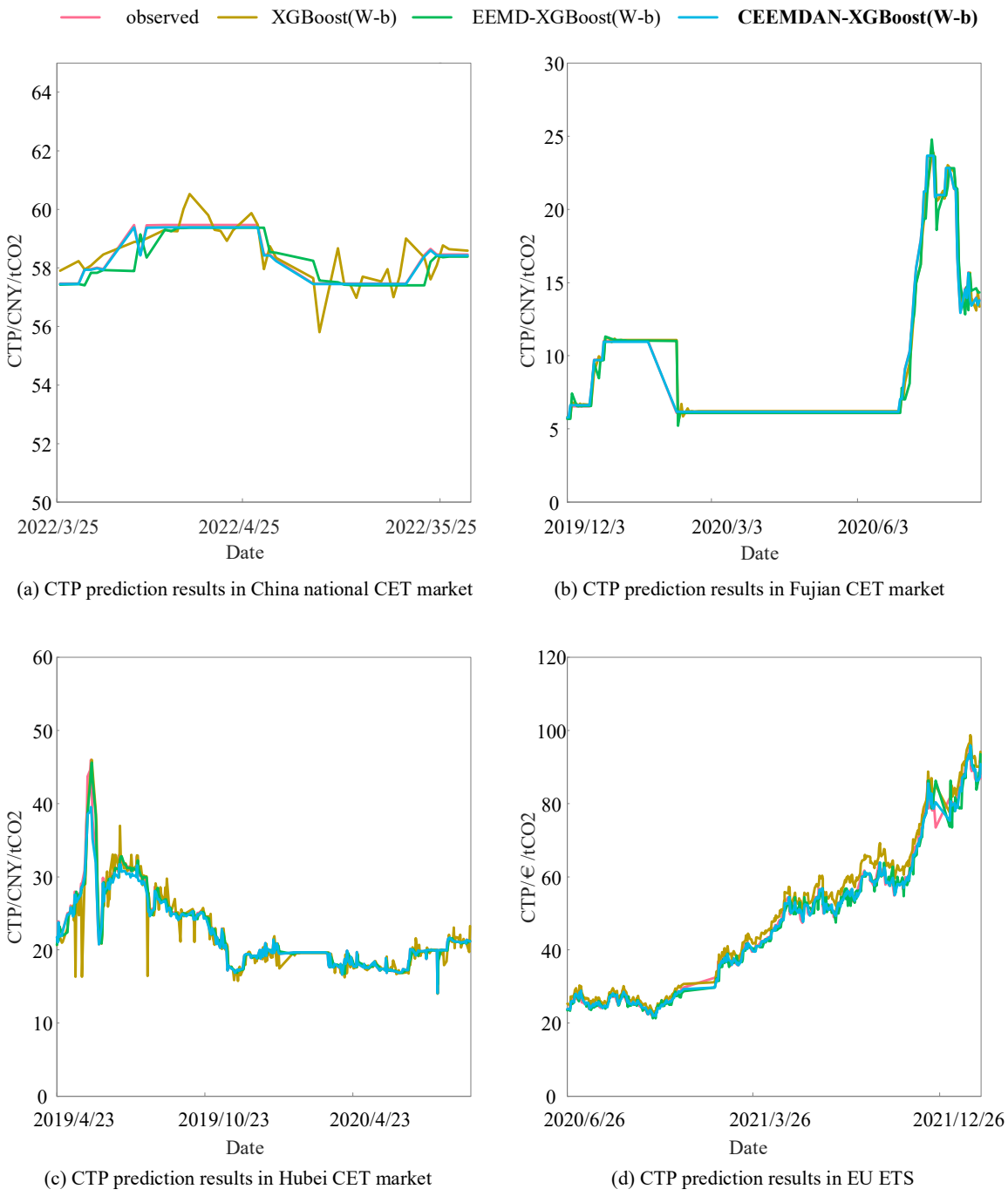


Figure 4. The decomposition result of the initial CTP for China's national CET market.

Through the decomposition of the CTP based on CEEMDAN algorithm, the initial CTP data is divided into seven IMFs and a residential. Of which, IMF1 to IMF5 present relatively random and disorderly complex volatility, IMF6 and IMF7 show obvious periodicity, and the residential is a smooth curve. Then, the decomposed components are put into the XGBoost(W-b) model to get the final prediction results. To verify the superiority of

CEEMDAN, the prediction results of XGBoost(W-b) without decomposition and EEMD-XGBoost(W-b) are used for comparison, as shown in Figure 5 and Table 6.



(a) CTP prediction results in China national CET market

(b) CTP prediction results in Fujian CET market

(c) CTP prediction results in Hubei CET market

(d) CTP prediction results in EU ETS

Figure 5. CTP prediction results for different decomposition methods.

As shown above, due to the volatility of CTP data and the difference in sample size, the prediction accuracy of each model in each market is significantly different. Of which, the CTP prediction error of China's national CET market ranges from 0.07% to 0.70%, the CTP prediction error of the Fujian CET market ranges from 0.64% to 2.68%, the CTP prediction error of thr Hubei CET market ranges from 0.64% to 3.14% and the CTP prediction error of the EU ETS ranges from 2.12% to 5.27% (from the perspective of MAPE). Although the market subjects studied are different, the predicted ranking of each model remains: CEEMDAN-XGBoost(W-b) > EEMD-XGBoost(W-b) > XGBoost(W-b)

without decomposition methods. Compared to other algorithms, the decrease in prediction error of CEEMDAN-XGBoost(W-b) is shown in Table 7.

Table 6. The error of the forecasting models based on different decomposition methods.

China's National CET Market	**MAE**	**MAPE**	**RMSE**
XGBoost (W-b)	0.41	0.70%	0.56
EEMD-XGBoost (W-b)	0.24	0.40%	0.42
CEEMDAN-XGBoost (W-b)	**0.04**	**0.07%**	**0.05**
Fujian CET market	**MAE**	**MAPE**	**RMSE**
XGBoost (W-b)	0.37	2.68%	0.75
EEMD-XGBoost (W-b)	0.36	2.30%	0.88
CEEMDAN-XGBoost (W-b)	**0.07**	**0.64%**	**0.07**
Hubei CET market	**MAE**	**MAPE**	**RMSE**
XGBoost (W-b)	1.01	3.14%	1.84
EEMD-XGBoost (W-b)	0.64	1.99%	1.16
CEEMDAN-XGBoost (W-b)	**0.26**	**0.64%**	**0.74**
EU ETS	**MAE**	**MAPE**	**RMSE**
XGBoost (W-b)	2.60	5.27%	3.16
EEMD-XGBoost (W-b)	1.41	2.84%	2.02
CEEMDAN-XGBoost (W-b)	**1.03**	**2.12%**	**1.46**

Table 7. The decrease in prediction error of CEEMDAN-XGBoost(W-b) compared to other algorithms.

CET Market	**Prediction Error Decrease Proportion (%)**
China's national CET market	81.58~89.28
Fujian CET market	72.10~76.06
Hubei CET market	67.71~79.52
EU ETS	25.24~59.71

4.4. Discussion

According to the comparison results of multiple prediction models, several conclusions can be obtained:

(1) When dealing with small samples and low volatility data, traditional machine learning algorithms (BP and LSSVM) have the same prediction performance as deep learning algorithms (LSTM and GRU). However, BP is prone to fall into the problem of local optimum [42], and LSSVM is more suitable for dealing with small sample problems. When forecasting for three carbon markets other than China's national CET market, the accuracy of their forecasts decreases significantly.

(2) Although the deep learning models perform better than the traditional models, they also face problems of low computation efficacy. Moreover, deep learning algorithms perform multi-timestep prediction mainly based on multi-output regressor (MOR), which implies multiple mechanical iterations of the single-output regression problem, with the result that the model does not benefit from the underlying relationships between the target variables. Through the windowing process in this paper, the "group prediction" of future CTP can be realized, which helps to capture the autocorrelation effect in the target variable and makes up for the defect of multi-output independent prediction [28].

(3) The decomposition effect of the EEMD approach is primarily determined by the number of integrations. CEEMDAN can effectively solve this problem by adding a finite number of times of adaptive white noise, improving the decomposition effect and increasing prediction accuracy [43]. This is also why CEEMDAN–XGBoost(W-b) outperforms EEMD–XGBoost(W-b) in all carbon markets in terms of prediction accuracy and forecasting ability.

5. Conclusions and Future Work

5.1. Conclusions

With the increasingly serious problem of climate change, the carbon market has become the focus of scholars' attention, and CTP prediction is one of the main research directions. On the one hand, some previous studies have proven that the advantages of deep learning algorithms have relatively strict application conditions (sample size, data randomness and volatility), and significantly increase the complexity of network structure and operation time. On the other hand, due to the difference of social and economic environments, different carbon markets show completely different development laws, which lead to the difference in CTP data. Under this background, a novel hybrid prediction algorithm based on CEEMDAN and XGBoost(W-b) is proposed in this paper, and the following conclusions can be obtained:

(1) The sample size and volatility of the data will significantly affect the prediction accuracy of the model. The proposed model shows high universality and superiority through the simulation analysis of CTP data of four typical CET markets.
(2) By windowing the input structure of the traditional XGBoost model, the prediction accuracy has been significantly improved. XGBoost(W-b) has shown better prediction accuracy compared with traditional machine learning algorithms and state-of-the-art deep learning algorithms in all the CET markets studied in this paper.
(3) The introduction of decomposition algorithm can greatly reduce the volatility and randomness of the initial CTP data, thus improving the performance of the prediction model.

5.2. Limitations and Future Work

The aim of this paper is to prove that simple but powerful ensemble models such as XGBoost can also exceed many deep learning models in time series forecasting, only by slightly configuring input processing structures. Therefore, the benchmark model is mainly selected from classical deep learning algorithms such as LSTM and GRU. In recent years, more complex and efficient deep learning algorithms have also been proposed. However, some of the code and data are not open access, which leads to the difficulty of reproducing the prediction effect of models. This is one of the limitations of this paper, which may lead us to overestimate the proposed algorithms. In our future work, we will work on two main aspects: first, we will try to combine the proposed windowing process with other algorithms (such as LSSVM, BP). Second, we will further extend the scope of the compared benchmark deep learning algorithms to get more reasonable results.

In addition, since the CTP data of some carbon markets (such as the United States and Switzerland) are on a quarterly basis, the volatility and the sample size of the data are difficult to meet the requirements of this paper. Therefore, based on the comprehensive consideration of data availability and validity, four CET markets with typical characteristics were selected as the objects of empirical analysis. The effects of the proposed model in other markets will be further explored in future studies.

Author Contributions: Conceptualization, Y.Z.; methodology, Y.Z.; resources, C.Z.; writing—original draft preparation, C.Z.; writing—review and editing, Y.Z.; supervision, H.Z.; project administration, H.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This study is supported by the Natural Science Foundation of China under Grant No. 71973043.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors are grateful to the editor and anonymous reviewers for their work.

Conflicts of Interest: The authors declare no conflict of interest.

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