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Modeling Carbon Emission Allowance Prices Using Multi-Scale Decomposition and Integrated Deep Learning Approaches

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Abstract: Carbon trading, as the critical market mechanism to achieve greenhouse gas emotion reduction, have received more attention around the world. The target that China establish and improve Carbon Emissions Trading Exchange (CCET) in recent year is to help the achievement of “peak carbon dioxide emissions”, “carbon neutrality”. However, Considering the characteristics of nonlinearness, strong fluctuation of carbon price, the accuracy of data prediction reduced significantly. Based on China Carbon Emissions Trading Exchange (CCET) data from July 2021 to March 2025, this paper build a multi-factor hybrid forecasting model that integrates VMD-CEEMDAN decomposition with GARCH-MIDAS and CNN-BiLSTM-Attention model throughout the ARCH and Sample Entropy as testing methods. Meanwhile, this model introduce influence factor including Macro Economy, Similar Products, Energy Structure and Climate Environment. Combine the random forest method with the MIDAS approach to select and integrate multi-frequency influencing factors, and evaluate model performance using indicators such as MAE, MSE, and RMSE. The experimental results show that the proposed model is better than the other model in accuracy and stability. The indicators including MAE, MSE and RMSE all are less than other comparison models.

Keywords: CNN-BiLSTM-Attention; VMD; CEEMDAN; GARCH-MIDAS; Carbon Price Prediction.

1. Introduction

In 2020, President Xi Jinping made a major declaration at the 75th United Nations General Assembly, stating that China will strive to achieve "carbon peak" before 2030 and work towards achieving "carbon neutrality" before 2060. As the world's largest emitter of carbon, China has consistently fulfilled its carbon reduction responsibilities and has gradually explored and constructed a more mature and comprehensive carbon emissions trading market in recent years. In October 2011, the National Development and Reform Commission issued the "Notice on the Pilot Carbon Emissions Quota Trading," which identified seven pilot carbon emissions trading market regions, including Beijing, Shanghai, Tianjin, Guangdong, Chongqing, Hubei, and Shenzhen. In 2017, the "National Carbon Emissions Quota Trading Market Construction Plan (Power Generation Industry)" was further issued, and in 2021, the national carbon emissions trading market officially launched. By the end of 2024, the total transaction volume of carbon quotas on the national carbon emissions trading market reached 630 million tons, with a total transaction value of 43.033 billion yuan, making it the largest carbon emissions trading market in the world. However, China still faces a series of challenging tasks, such as economic development, improving people's livelihoods, pollution control, and ecological protection. The problem of unbalanced and inadequate development remains prominent, and there are still many bottlenecks in promoting high-quality development. This not only requires active improvements in technology, energy, and climate environments but also demands concerted efforts across society. Achieving this goal will help promote the rapid development of China's carbon finance sector and establish a sound economic system for low-carbon circular development. Currently, with the rapid development of carbon emissions trading markets worldwide, research on the selection of factors influencing carbon emissions trading prices and their role in price forecasting has also become an important topic of discussion for policymakers, think tanks, and academia.

On one hand, regarding the influencing factors of carbon emissions trading prices, traditional studies primarily focus on macroeconomic conditions, similar products, energy prices, and atmospheric conditions. For example, Du Ziping and Liu Fuchun [8] used a GA-BP neural network model and MIV method to analyze the impact and extent of energy prices on the carbon prices in five regional markets in China, and the results showed that energy prices were the major influencing factor. Wei Yu, Zhang Jiahao, and Chen Xiaodan [9] employed various classic forecasting models and DMS and DMA analysis to examine multiple factors and their impact on forecasting. They found that macroeconomic conditions, financial trends, international carbon emissions trading prices, and atmospheric conditions had a significant impact on China's carbon emissions trading prices, while the impact of international fossil energy prices (such as crude oil) on China's carbon emissions trading prices was gradually decreasing. Qiao Ning, Zhang Chao, Zhang Jisheng, and Chen Haidong [3] used MIV (Mean Impact Value) in the GA-BP neural network to perform variable selection on related influencing factors and found that WTI crude oil prices had the greatest impact on the national carbon emissions trading prices, with an average impact value of 0.0825, which was highly positively correlated. Additionally, some recent studies have made new attempts. For example, Wu [13] incorporated the Li Keqiang Index and coke prices into the study of China's carbon emissions trading market for the first time, and found that these factors had large characteristic values and strong explanatory power on carbon emissions trading prices. Wang Na [7] introduced the Baidu Search Index, Consultation Index, etc., to construct a DMNP model, which demonstrated good forecasting performance.

On the other hand, regarding carbon emissions trading price forecasting, existing research mainly focuses on two types of models: one is traditional econometric models, primarily including GARCH, VAR, etc.; the other is artificial intelligence-based machine learning models, mainly using RNN, CNN, LSTM, etc. For example, in the case of traditional econometric models, Gong Weifeng et al. [4] used the GARCH-BP model to study the carbon emissions trading price returns in five provinces and found that only Guangdong showed a positive correlation between return and risk. From the perspective of volatility characteristics, Guangdong's carbon trading market had the highest level of development. Zhou and Li [11] used the VAR (Vector Autoregression) and VEC (Vector Error Correction) models to study the Hubei carbon emissions trading market. Their model explored the dynamic relationships between carbon emissions trading prices and air quality indicators, fossil energy prices, and macroeconomic indicators. The empirical results showed a long-term equilibrium relationship between carbon emissions trading prices and these indicators. In addition, they also used the GARCH model to investigate the volatility characteristics of carbon emissions trading prices and found that the returns of carbon emissions trading prices exhibited phenomena such as volatility clustering, fat tails, and asymmetric distributions, similar to financial time series. Regarding machine learning models, Wei Binglin et al. [5] built a Transformer-LSTM multi-factor carbon emissions trading price forecasting model for Hubei data and compared it with SVR, MLP, LSTM, and Transformer models. The empirical results showed that the proposed model's predicted prices were closer to actual prices and performed better in MAE, MSE, and RMSE. Sun and Xu [10] adopted the EEMD-LDWPSOwLSSVM model to forecast the carbon emissions trading prices of the Shanghai, Guangdong, and Hubei markets. The empirical results showed that this model could be applied perfectly to the three markets.

Furthermore, to enhance prediction performance, it is particularly important to process the noise within carbon emission trading data, with decomposition-based denoising being the primary method for noise handling. Commonly used data decomposition methods include Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Complementary Ensemble Empirical Mode Decomposition (CEEMD), Empirical Mode Decomposition (EMD), and Variational Mode Decomposition (VMD), among others. Sun and Huang [12], in their research on carbon emission trading price prediction, employed a hybrid model integrating Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), and LSTM, applying it to eight carbon emission trading markets in China. The empirical results collectively indicate that this model exhibits high prediction accuracy and robustness. Additionally, they concluded that data subjected to a second round of modal decomposition can more effectively improve prediction accuracy. Wu Lili and Tai Qingrui [2] proposed a GA-VMD-CNN-BiLSTM-Attention model for the Hubei market and, on this basis, incorporated interval prediction. The results show that their model achieved optimal prediction performance. Duan Juntao [1] introduced the Sparrow Search Algorithm (SSA), combined it with Gated Recurrent Unit (GRU) and CEEMDAN, and proposed the CEEMDAN-SSA-GRU model. The results demonstrate its capability to accurately predict carbon price data across different regions and time scales. Zhang Xing [6] conducted an empirical study on data from Hubei Province using secondary decomposition and machine learning models like OLS-FEEMD-WD-COMBI, attaining high prediction accuracy.

In empirical analysis, this paper selects the national carbon emissions trading market trading prices from July 2021 to March 2025 as the sample and proposes a carbon emissions trading price forecasting method based on VMD-CEEMDAN denoising and the GARCH + CNN-BiLSTM-Attention hybrid model. The possible contributions of this paper are as follows: First, most current studies focus on pilot markets, with fewer scholars researching national carbon emissions trading markets. This paper uses the national carbon emissions trading market data from 2021 to 2025 to improve the carbon emissions pricing mechanism. Additionally, it incorporates the coke price index, EPU, the new Li Keqiang Index, and SO, which makes the conclusions of this paper more instructive. Finally, while existing literature mainly uses either traditional econometric models or machine learning models to study carbon prices independently, this paper reconstructs high-frequency and low-frequency sequences through ARCH tests and sample entropy, and constructs a GARCH-MIDAS-CNN-BiLSTM-Attention carbon emissions pricing model. The GARCH model is used for high-volatility data, and the CNN-BiLSTM-Attention model is used for low-volatility data, which enhances the persuasiveness of the model.

2. Carbon Emissions Trading Price Forecasting and Empirical Analysis of Influencing Factors

(1) Variable Selection and Descriptive Analysis

This paper comprehensively selects 11 datasets, including the national carbon emissions trading price. The national carbon emissions trading price from July 2021 to March 2025 is chosen as the dependent variable. The explanatory variables include macroeconomic factors such as the US dollar exchange rate, Consumer Price Index (CPI), Purchasing Managers' Index (PMI), Li Keqiang Index, and Economic Policy Uncertainty Index (EPU), as well as the CSI 300 Index Climate and environmental factors include sulfur dioxide (SO), PM2.5, average monthly temperature, and AQI (Air Quality Index). For similar product factors, the EU benchmark carbon allowance futures contract price (EUA) and Certified Emission Reductions (CERs) are used. Energy structure factors include the coking coal index, coke price index, and the oil and natural gas price index. The descriptive analysis of the explanatory variables is shown in Table 1 below.

Table 1. Descriptive Statistics of Influencing Factors

Variable	Mean	Std.	Max	Min
Carbon Emissions Trading Price	65.93	16.03	104.25	41.46
US Dollar Exchange Rate	6.87	0.31	7.35	6.30
Coking Coal Index	2076.18	453.55	3303.20	1341.30
Coke Price Index	2598.95	615.47	4090.50	1544.50
EUAs	75.78	11.14	97.58	50.5
Sulfur Dioxide	2.94	1.44	10	1
PM2.5	33.57	30.46	180	0
Li Keqiang Index	7.33	1.97	14.3	5.49
Consumer Price Index	100.071	0.14	101	99
Purchasing Managers' Index	50.96	2.73	57	42.6
Economic Policy Uncertainty Index	284.20	81.69	516.98	124.29
Oil and Natural Gas Price Index	4630.26	1310.42	6477.96	2782.58
CSI 300 Index	3848.79	535.47	4576.52	3092.47
Certified Emission Reductions	0.29	0.14	0.29	0.01
Average Monthly Temperature	18.11	4.18	23.28	11.69
Air Quality Index	78.49	18.23	102.54	52.33

(2) Feature Importance Selection of Influencing Factors

The main purpose of feature selection is to reduce the complexity of the model, mitigate overfitting, and improve computational efficiency. This paper primarily uses the feature ranking based on the Random Forest method for feature selection. When forecasting carbon emissions trading prices, the importance values of different features vary for different categories of influencing factors. However, considering previous research biases and the completeness of the influencing factors, this study selects 1-2 representative variables from each of the four categories. The detailed feature importance ranking is shown in Table 2.

Table 2. Feature Importance Ranking of Influencing Factors for Carbon Emissions Trading Price

Variable		Importance
Macroeconomic Factors	US Dollar Exchange Rate	0.007507
	Li Keqiang Index	0.070626
	Consumer Price Index	0.003617
	EUA	0.222489
	PMI	0.008321
	CSI 300 Index	0.009281
Natural Environment Factors	PM2.5	0.001873
	SO	0.00085
	AQI	0.00043
	Average Temperature	0.00076
Energy Structure Factors	Coking Coal Index	0.176952
	Coke Price Index	0.044325
	Oil and Natural Gas Price Index	0.627889
Similar Product Factors	EPU	0.012502
	CERs	0.007581

For macroeconomic factors, EUA and the Li Keqiang Index have the largest feature importance values and provide a strong explanatory power for the carbon emissions trading price. For natural environmental factors, PM2.5 has the highest feature value. Regarding energy structure factors, the Coke Price Index has a much higher feature value than the Oil and Natural Gas Price Index and the Coking Coal Index. For similar product factors, this paper selects EPU (Economic Policy Uncertainty Index) as the representative variable.

In summary, the selected explanatory variables for the model are: Li Keqiang Index, China Economic Policy Uncertainty Index (EPU), PM2.5, Coke Price Index, and EUA.

(3) Multi-Scale Decomposition and Sample Entropy Test

VMD (Variational Mode Decomposition) seeks the optimal solution of the search model through an iterative process, which can effectively handle and resolve the mode mixing problem that occurs in EMD (Empirical Mode Decomposition) and EEMD (Ensemble Empirical Mode Decomposition). In this paper, the VMD function in the vmdpy signal module is used to decompose the carbon emissions trading price.

To avoid under- or over-decomposition after the VMD process, it is necessary to determine the value of K for the decomposition. Considering that the center frequencies of the modes after VMD decomposition are different from each other, the decomposition is carried out for K = 2, 3, ..., 10, and the corresponding center frequencies are calculated. After computation, K = 8 is selected as the parameter for the VMD decomposition. For other parameters, alpha is set to 1500, and tau is set to 0. The decomposition results of the national carbon emissions trading price using VMD are shown in Figure 1.

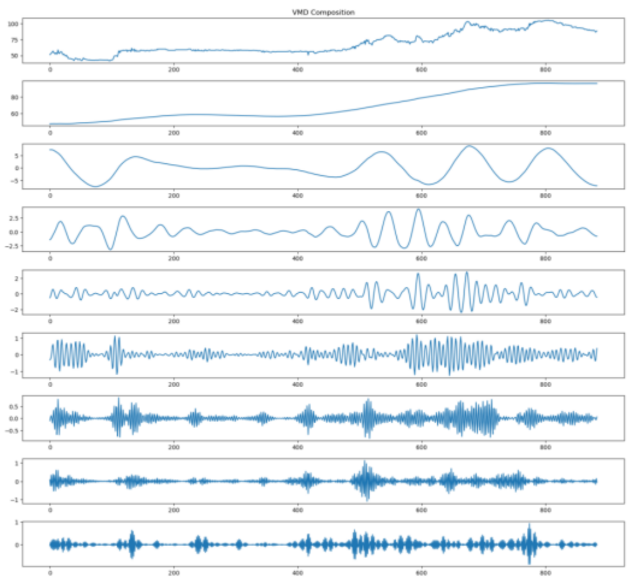

Figure 1. VMD Decomposition Results of the National Carbon Emissions Trading Price

The sample entropy is calculated using the Sampen module in Python. Generally speaking, the larger the sample entropy, the more complex the data is. From the table, it can be observed that the sample entropy values of IMF4, IMF7, and IMF8 are higher than the sample entropy values of the other components, indicating that these three components are more complex. Therefore, IMF4, IMF7, and IMF8 are classified as high-frequency sequences.

Table 3. Sample Entropy Test Results for VMD Decomposition

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
SE	0.0062	0.1270	0.3115	0.4607	0.3292	0.3854	0.4910	0.4518

In this paper, the three data components with larger sample entropy values, IMF4, IMF7, and IMF8, are subjected to CEEMDAN decomposition. Using the PyEMD module in Python, the CEEMDAN decomposition is performed. The decomposition of IMF4, IMF7, and IMF8 results in 8 components for IMF4, 9 components for IMF7, and 9 components for IMF8, as shown in Figure 2. Thus, after the VMD-CEEMDAN double decomposition, the carbon emissions trading price data is divided into a total of 31 components.

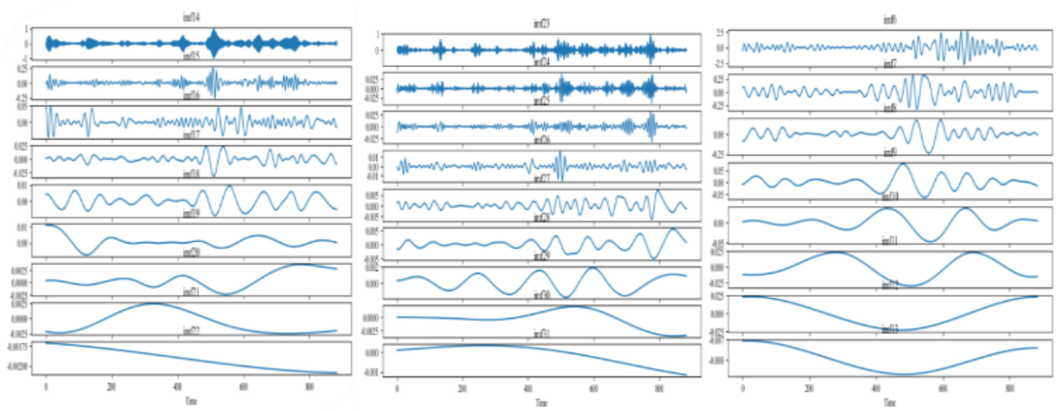

Figure 2. Results of the Double Decomposition

To distinguish the components, the 31 components obtained from the VMD-CEEMDAN double decomposition are labeled as IMFi', where i = 1, 2, ..., 31. After CEEMDAN decomposition, the original components IMF4, IMF7, and IMF8 correspond to IMFi' = 6, 7, ..., 13, IMFi' = 14, 15, ..., 22, and IMFi' = 23, 24, ..., 31, respectively. The corresponding sample entropy values are shown in the figure. The sample entropy values of all components decrease to below 0.4, proving that the double decomposition further reduces the complexity of the data, providing a possibility for improving the prediction accuracy in subsequent steps.

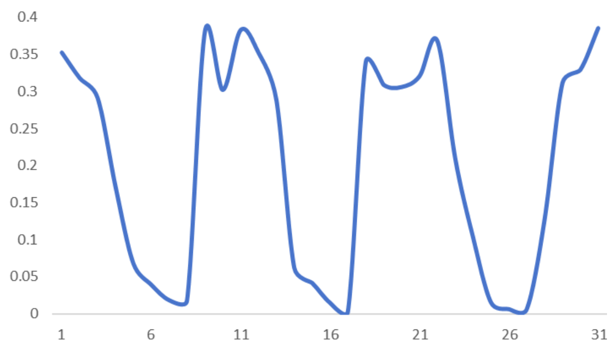

Figure 3. Sample Entropy Values of Each Component After VMD-CEEMDAN Double Decomposition

(4) ARCH Effect Test

To distinguish between high-frequency and low-frequency sequences, this paper classifies the frequency bands based on the presence of the ARCH effect and sample entropy. Bands with an ARCH effect and sample entropy greater than 0.25 are classified as high-frequency sequences, while bands without an ARCH effect and sample entropy less than 0.25 are classified as low-frequency sequences.

First, a stationarity test is conducted on the 31 frequency bands. According to the ADF test, 5 of the 31 bands exhibit non-stationary characteristics, while the other modes do not have a unit root, indicating they are stationary sequences. The Ljung-Box test (LB test) is then used to determine if the data after double decomposition forms a white noise sequence. From Table 4, it can be observed that the results for each component's lag value of 10 are all 0, which leads to the rejection of the null hypothesis in favor of the alternative hypothesis, meaning that each component is not a white noise sequence and exhibits ARCH effects.

Table 4. LB Values for Each Component After VMD-CEEMDAN Processing with a 10-Lag Period for the National Carbon Emissions Trading Price

	IMF1	IMF2	……	IMF30	IMF31
1	1.12E-168	8.31E-187	……	9.31E-77	6.98E-08
2	3.95E-270	0	……	4.49E-84	2.55E-167
3	2.71E-305	0	……	2.89E-226	2.39E-214
……	……	……	……	……	……
8	0	0	……	0	0
9	0	0	……	0	0
10	0	0	……	0	0

Meanwhile, given that the sample entropy test has been conducted on all the decomposed frequency bands, this paper classifies the bands according to the established criteria. Sequences with higher sample entropy and greater structural complexity are classified as high-frequency sequences: IMFi'i=3, 4, 5, 6, 7, 8, 14, 15, 16, 17, 18, 23, 24, 25, 26, 27. Sequences with lower sample entropy are classified as low-frequency sequences: IMFi'i=1, 2, 9, 10, 11, 12, 13, 19, 20, 21, 22, 28, 29, 30, 31.

3. Model Construction and Results Analysis

Based on existing research in related literature, this paper selects the GARCH-MIDAS model for analyzing and predicting high-frequency sequences, and the CNN-BiLSTM-Attention model for analyzing and predicting low-frequency sequences. Among them, GARCH (1, 1) is already sufficient to capture the ARCH effect, so GARCH (1, 1) is used for fitting. Additionally, the data is divided into training and testing sets at an 8:2 ratio.

(1) GARCH-MIDAS

The GARCH-MIDAS model is used to analyze and process high-frequency sequences. The maximum lag order Kfor MIDAS is set to 12, meaning that the data for the following year is used to obtain long-term volatility. The model is then parameterized, and the parameter estimation results are shown in Table 5:

Table 5. GARCH-MIDAS parameter table

	α	β	μ	ω	θ
GARCH-MIDAS	0.654694 (0.0000)	0.307966 (0.0000)	-0.062666 (0.09784)	5.244399 (0.052718)	0.270037 (0.246486)

Based on the results in the table, it can be observed that the parameters α, β, and ω of the decomposed carbon emissions trading price meet the significance level. However, the parameters μ and θ do not generally pass the significance level. The primary reason for this is the influence of extreme values in several data columns. If these extreme values are removed, the parameters would meet the significance level. Overall, the model's parameters are generally significant. The model's performance is depicted by the comparison of the predicted values with the actual values' mean. The training results are as follows: it can be seen that the predicted values follow the same trend as the actual values, and R2is 0.90598, indicating a good fit.

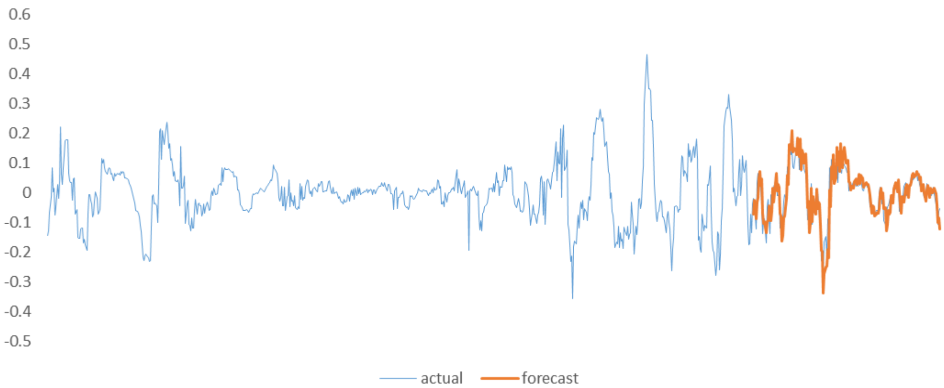

Figure 4. GARCH-MIDAS Fitting Plot

(2) CNN-BiLSTM-Attention

The CNN-BiLSTM-Attention model is used to analyze and process the low-frequency sequences. In this model, the activation function for CNN is ReLU, for BiLSTM is softsign, and for Attention is softmax. Since BiLSTM is a bidirectional memory model, a learning window needs to be defined. Given that the national carbon emissions trading market began in July 2021 and the data volume until March 2025 is not very large, the longer the window, the better the training effect. Therefore, the learning window is set to 0.2 times the total number of data points for the national carbon emissions trading price.

To prevent overfitting, the learning rate is set to 0.01, and the number of training iterations is set to the sample size of the carbon emissions trading price. The MAE (Mean Absolute Error) function is used to evaluate the training process. The results show that the training effect is consistent with the price trend, with an R^2 value of 0.959, indicating excellent fit.

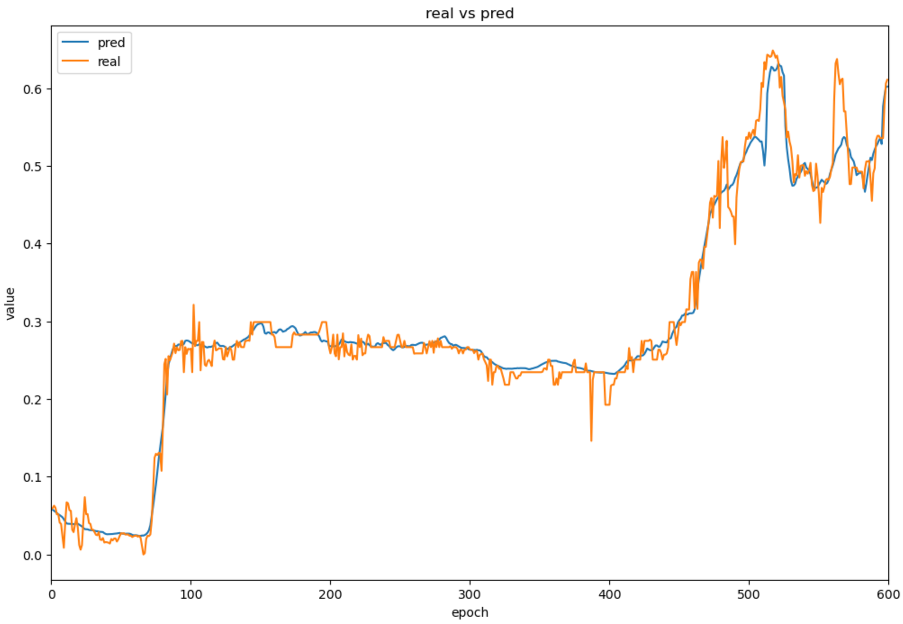

Figure 5. CNN-BiLSTM-Attention Fitting Plot

(3) Comparative Analysis

To verify the superiority of the proposed model, several other models are used for comparison. The results are shown in Table 6.

Model 1: BiLSTM for prediction.

Model 2: GARCH-MIDAS for prediction.

Model 3: VMD-BiLSTM for prediction.

Model 4: VMD-GARCH-MIDAS for prediction.

Model 5: CNN-BiLSTM-Attention for prediction.

Model 6: VMD-CEEMDAN-GARCH-MIDAS for prediction.

Model 7: VMD-CEEMDAN-CNN-BiLSTM-Attention for prediction.

Model 8: VMD-CEEMDAN-GARCH-MIDAS-CNN-BiLSTM-Attention for prediction,

which is the model proposed in this paper. The parameters of the comparison models are set according to those in the proposed model.

Table 6. Comparative Analysis Chart

Model	MSE	RMSE	MAE
VMD-CEEMDAN-GARCH-MIDAS-CNN-BiLSTM-Attention	0.0008238	0.042154	0.0300095
VMD-CEEMDAN-CNN-BiLSTM-Attention	0.004	0.0631	0.0468
VMD-CEEMDAN-GARCH-MIDAS	0.13573296	0.108056	0.086528
VMD-BiLSTM	0.008477	0.074896	0.057291
CNN-BiLSTM-Attention	0.0059038	0.076836	0.049031
BiLSTM	2.069081	1.43843	1.053928
GARCH-MIDAS	0.303	1.203203	0.781543
VMD-GARCH-MIDAS	0.050848	0.241726	0.194935

As shown in the table, the VMD-CEEMDAN-GARCH-MIDAS-CNN-BiLSTM-Attention model constructed in this paper has lower MSE, RMSE, and MAE values compared to the other comparison models, indicating that the accuracy of this model is significantly better than the others.

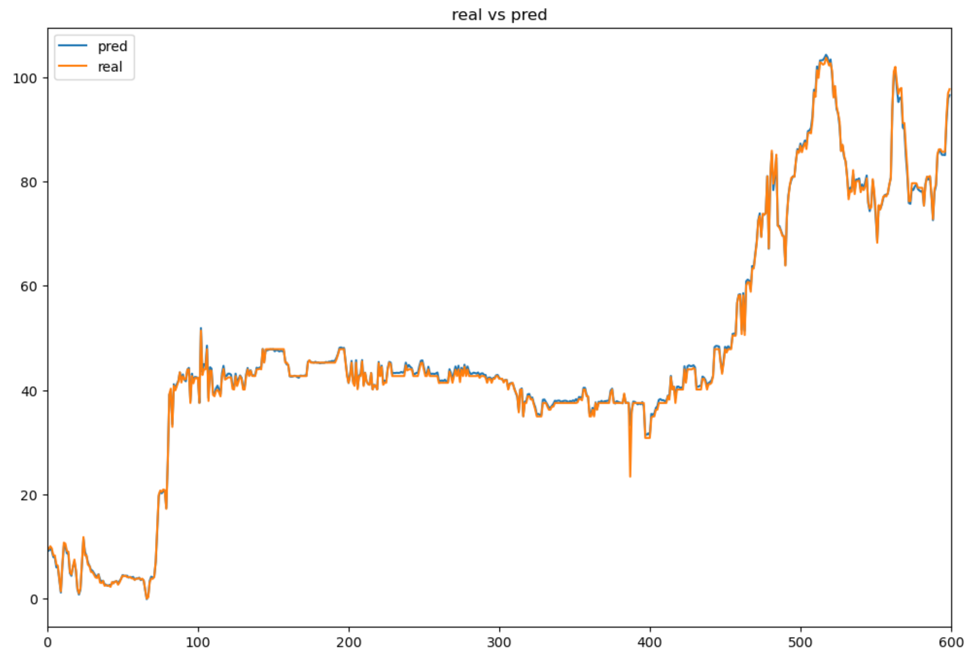

Figure 6. Hybrid Model Prediction Results

4. Conclusion

With the increasing maturity of the carbon emissions trading market, the prediction and pricing of carbon emissions trading prices have gained more attention. However, due to issues such as high volatility, exogeneity, and multicollinearity, predicting these prices remains a significant challenge. Based on this, this paper constructs a multi-factor hybrid prediction model that integrates VMD-CEEMDAN decomposition with GARCH-MIDAS and CNN-BiLSTM-Attention modeling. By introducing macroeconomic, energy structure, and climate variables, combined with Random Forest and MIDAS methods for feature selection and fusion of multi-frequency influencing factors, the model optimizes parameters using Maximum Likelihood Estimation. Model performance is evaluated using indicators such as MAE, MSE, and RMSE, and compared with seven other models, including VMD-CEEMDAN-GARCH-MIDAS, VMD-CEEMDAN-CNN-BiLSTM-Attention, and others.

Empirical results show that the VMD-CEEMDAN-GARCH-MIDAS-CNN-BiLSTM-Attention model proposed in this paper performs the best in prediction. This indicates that combining traditional econometric models with machine learning can improve predictive performance and highlights that diverse data require appropriate models to fully realize their potential. This paper provides new ideas for predicting carbon emissions trading prices in terms of model design and data selection. It is beneficial for policymakers to understand the fluctuations in carbon emissions trading prices, establish a stable, effective, and reasonable carbon pricing mechanism, and can also provide a basis for investors to make informed decisions, reduce price risks, and promote the healthy development of China's carbon trading market.

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