Petroleum Science 22 (2025) 5314–5328

Contents lists available at ScienceDirect

Petroleum Science

journal homepage: www.keaipublishing.com/en/journals/petroleum-science

Original Paper

Forecasting carbon price using a hybrid framework based on Bayesian optimization algorithm

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ARTICLE INFO

Article history:
Received 28 April 2025
Received in revised form
9 July 2025
Accepted 13 October 2025
Available online 21 October 2025

Edited by Min Li

Keywords:
Carbon price forecasting
ICEEMDAN
GRU
CNN
LSTM
Bayesian optimization

ABSTRACT

With the European Union (EU) introducing the Carbon Border Adjustment Mechanism (CBAM), accurately forecasting EU carbon price is crucial for exporters to estimate export costs, plan low-carbon strategies, and mitigate trade risks. In the petroleum sector, carbon pricing directly influences upstream investment returns and carbon intensity targets, thereby closely linking emissions markets with fossil energy strategies. Existing models often fail to fully capture the nonlinear, non-stationary nature of carbon prices and their dependence on external factors. This study proposes a novel hybrid framework that combines improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) with gated recurrent unit-convolutional neural network-long short-term memory network-Bayesian optimization (GRU-CNN-LSTM-BO). Empirical results based on the EU emissions trading system (ETS) market demonstrate that the proposed model significantly improves forecasting accuracy. Among all experiments, the proposed GRU-CNN-LSTM-BO framework achieves the best performance, yielding the lowest MAE (1.3872), RMSE (1.7038), MAPE (0.0166), and MSPE (0.0004), as well as the highest R^2 (0.9400). Compared to all benchmark models, the GRU-CNN-LSTM-BO model achieves reductions in MAE and RMSE ranging from 5.38% to 63.65% and 8.97% to 64.41%, respectively. To further validate the generalization ability and predictive performance of the proposed model, it is also applied to China's ETS. The results show that the GRU-CNN-LSTM-BO model also performs very well in China's ETS.

1. Introduction

Climate change and global warming caused by greenhouse gas emissions pose significant threats to the human living environment (Bashmakov et al., 2022). In response to this climate crisis, many countries have taken measures to reduce carbon emissions through formulating climate policies and implementing technological solutions. Carbon markets, as an important policy tool, play a crucial role in global carbon emission reduction (Wu et al., 2023). In order to fulfill the emission reduction targets of the Kyoto Protocol, the European Union (EU) established the world's first carbon emissions trading system (ETS) in 2005 (Ellerman et al., 2016). Subsequently, the Paris Agreement drove the EU ETS into a new phase of reform aimed at strengthening its effectiveness and alignment with long-term climate goals (An et al., 2021). Currently, the EU ETS is the largest and most mature market in the world, and its trading scale and liquidity have a significant impact on the global market. The core element of the ETS is the carbon price (Hintermayer, 2020). Accurate prediction of carbon price in the EU ETS has become increasingly important. In carbon-intensive sectors such as petroleum refining, gas-fired power generation, and petrochemical manufacturing, carbon price volatility directly affects marginal production costs and operational planning (Dai et al., 2022; Wang and Kuusi, 2024). Accurate carbon price forecasts can thus support more informed investment decisions, facilitate risk hedging strategies, and help design adaptive

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Peer review under the responsibility of China University of Petroleum (Beijing).

https://doi.org/10.1016/j.petsci.2025.10.010

compliance mechanisms (Lei et al., 2022; Zhang et al., 2025). Notably, the Carbon Border Adjustment Mechanism (CBAM) has been introduced under the Paris Agreement framework as a measure to prevent "carbon leakage." The CBAM directly links to EU carbon price, imposing costs on imports based on the difference between EU and foreign carbon prices (Pan et al., 2025). This mechanism not only reinforces the need for precise carbon price forecasts but also has significant implications for global trade. Therefore, reliable prediction of EU carbon price not only enhances market efficiency but also plays a strategic role in global trade policy within the new climate governance architecture.

1.1. Literature review

Carbon price forecasting can rely solely on historical data. However, such models often struggle to reflect sudden structural shifts or external shocks (Zhou et al., 2017). To improve forecasting performance, recent research on carbon price forecasting has also begun to focus on external influences, including macroeconomic indicators, energy prices, and climatic conditions (Mansanet-Bataller et al., 2007; Oberndorfer, 2009; Zheng et al., 2024). Sun and Wang (2020) found that external factors such as energy markets, exchange rates, macroeconomic indicators, and temperature changes have significant and systematic impacts on carbon price fluctuations. Building on existing studies, this study enhances the predictive capacity of carbon price models by accounting for a broader range of external influences.

The current methods on forecasting oil prices, gas prices, and carbon prices are mainly divided into two categories (Pan et al., 2022). The first category comprises statistical and econometric models, such as autoregressive integrated moving average (ARIMA) (Zhu and Chevallier, 2017), generalized autoregressive conditional heteroskedasticity (GARCH) (Dutta, 2018; Zhang et al., 2018), vector autoregressive (VAR) (Hintermayer, 2020), etc. With the development of artificial intelligence technology and statistical learning, researchers have gradually introduced machine learning models into the field of energy price prediction, such as gated recurrent unit (GRU) (Wang et al., 2021), long short-term memory neural network (LSTM) (Li et al., 2022), artificial neural network (ANN) (Atsalakis, 2016), etc. Zhang and Wen (2022) showed that temporal convolutional network (TCN) model prediction results outperform traditional statistical models and LSTM by multidimensional comparisons.

However, a single machine learning model still does not have enough predictive stability to meet researchers' expectations (Xu et al., 2025). Hybrid frameworks have gained prominence as an effective approach to enhance forecasting performance (Sun and Wang, 2020). Shi et al. (2024) proposed a hybrid convolutional neural network (CNN)-LSTM deep learning framework for carbon price forecasting and, through empirical analysis of China's Shenzhen pilot carbon market, demonstrated that the hybrid framework significantly outperformed standalone CNN and LSTM models.

More recently, researchers have enhanced hybrid frameworks by incorporating signal decomposition methods (Feng et al., 2023; Ji et al., 2019). Multiscale decomposition techniques, such as variational mode decomposition (VMD), decompose time series data into multiple independent modes, which are then modeled individually to improve forecasting accuracy (E et al., 2019). Jin et al. (2022) applied empirical mode decomposition (EMD) to split time series into intrinsic mode functions (IMFs) and trained a separate BPNN for each. This improved the prediction accuracy for individual components. However, the method modeled each IMF independently, overlooking potential interdependencies among components. Yang et al. (2024) utilized time-varying filtering empirical mode decomposition (TVF-EMD) to break down runoff sequences into components and further reconstructed components based on complexity before prediction, which reduced computational cost and improved overall forecast accuracy. With the widespread application of machine learning methods in energy forecasting, optimization algorithms have played an increasingly important role in enhancing the performance of predictive models (Davoodi et al., 2025; Meng et al., 2023). Wang et al. (2024) conducted experiments across multiple carbon markets, demonstrating that the Informer model optimized with Bayesian optimization and Hyperband (BOHB) outperforms the non-optimized model across all predictive metrics.

1.2. Research gaps and contributions

Despite substantial progress in carbon price forecasting, several key limitations remain. First, many existing studies rely on either traditional econometric models or standalone deep learning approaches (Huang et al., 2022; Zhang et al., 2018). They often fall short in capturing the nonlinear, non-stationary, and multi-scale characteristics of carbon price dynamics, limiting their ability to respond to sharp market fluctuations. Second, existing studies on decomposition-based time series forecasting typically apply decomposition algorithms to extract multiple IMFs. Separate predictive models are then built for each IMF before aggregating the outputs to reconstruct the final result (Cui and Niu, 2024; Li and Liu, 2023; Zhu et al., 2018). However, this strategy presents several challenges, as it requires managing and tuning multiple models, which increases computational complexity and modeling inconsistency (An et al., 2013). Moreover, it ignores potential interdependencies among components, which may contain joint informative structures, and it is vulnerable to error accumulation in the reconstruction stage, especially when some IMFs are not well predicted (Yang et al., 2024). Third, although hybrid frameworks such as GRU-CNN or CNN-LSTM have shown improved performance (Shi et al., 2024; Zhang et al., 2024a), they tend to focus on capturing either local spatial features or short-term temporal dependencies. They lack a comprehensive mechanism for modeling both long-term trends and high-frequency volatility. Furthermore, these models often depend on manual hyperparameter tuning (Wang et al., 2023), which can hinder model robustness and scalability in real-world carbon markets.

To address these gaps, this study proposes a hybrid forecasting framework that integrates advanced decomposition techniques, hybrid deep learning models, and automated hyperparameter optimization to enhance carbon price prediction accuracy. Improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) is applied to decompose the complex and non-stationary carbon price time series into IMFs, and then effectively isolate noise and capturing multi-scale patterns within the data (Yang et al., 2025). The resulting components are then transformed into lagged features and reconstructed to enhance signal clarity and retain multi-scale temporal features for unified model training. A hybrid GRU-CNN-LSTM model is employed to fully exploit both temporal and spatial features of the decomposed series. To overcome the limitations of manual parameter tuning, Bayesian optimization (BO) is integrated into the framework for systematically and efficiently fine-tuning the hyperparameters of the hybrid framework. By combining these techniques, this study presents a robust and adaptive carbon price prediction framework.

The main contributions of this article are as follows:

(1) A comprehensive index system is constructed, incorporating external factors such as macroeconomic indicators, energy

prices, exchange rates, and weather conditions for providing a holistic view of the factors influencing carbon price.

(2) It proposes a novel hybrid forecasting framework that integrates ICEEMDAN with a GRU-CNN-LSTM deep learning model, enabling effective noise reduction and robust spatial-temporal pattern learning. BO is employed to fine-tune hyperparameters, improving both the predictive accuracy and stability of the model.

(3) A unified modeling strategy based on lagged reconstruction of ICEEMDAN decomposed components is proposed to ensure effective noise reduction and to capture potential nonlinear interactions among components through a unified input structure.

The next sections are organized as follows: Section 2 presents the main methods utilized in this study. Section 3 describes the data collection and description. Section 4 outlines the experimental results analysis. Section 5 discusses the findings and extends the model to other markets. Finally, section 6 draws the conclusion of this study.

2. Methodology

2.1. The framework of this study

Fig. 1 illustrates the main framework of this study. The main steps are summarized as follows:

Step 1 Data collection and carbon price influencing factors selection. This study collects European Union Allowances (EUA) carbon futures price data along with a range of potential influencing factors, including macroeconomic indicators, energy prices, exchange rates, and weather conditions. Descriptive statistical analysis is conducted, and missing values are imputed using linear interpolation.

Step 2 Decomposition and reconstruction. The carbon price series is decomposed using the ICEEMDAN method, resulting in a set of IMFs and a residual. These components are then processed to generate lagged features. The lagged IMFs, combined with external variables, form a comprehensive dataset which is then split into training and testing sets. All variables are normalized to ensure comparability and improve model convergence.

Step 3 Experimental design and implementation. The experimental analysis in this study focuses on two main aspects. First, the predictive performance of the proposed GRU-CNN-LSTM model is compared with five benchmark models, including standalone GRU, CNN, LSTM, and hybrid models such as GRU-CNN and CNN-LSTM. Second, the effectiveness of BO is assessed by analyzing the performance of the GRU-CNN-LSTM model before and after hyperparameter tuning, highlighting the improvements in accuracy and robustness achieved through automated optimization.

Step 4 Model evaluation. All forecasting results are evaluated using five commonly used metrics (Table 1): mean squared percentage error (MSPE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). Generally, lower values of MSPE, RMSE, MAE, and MAPE, and a higher value of R^2 indicate better forecasting performance.

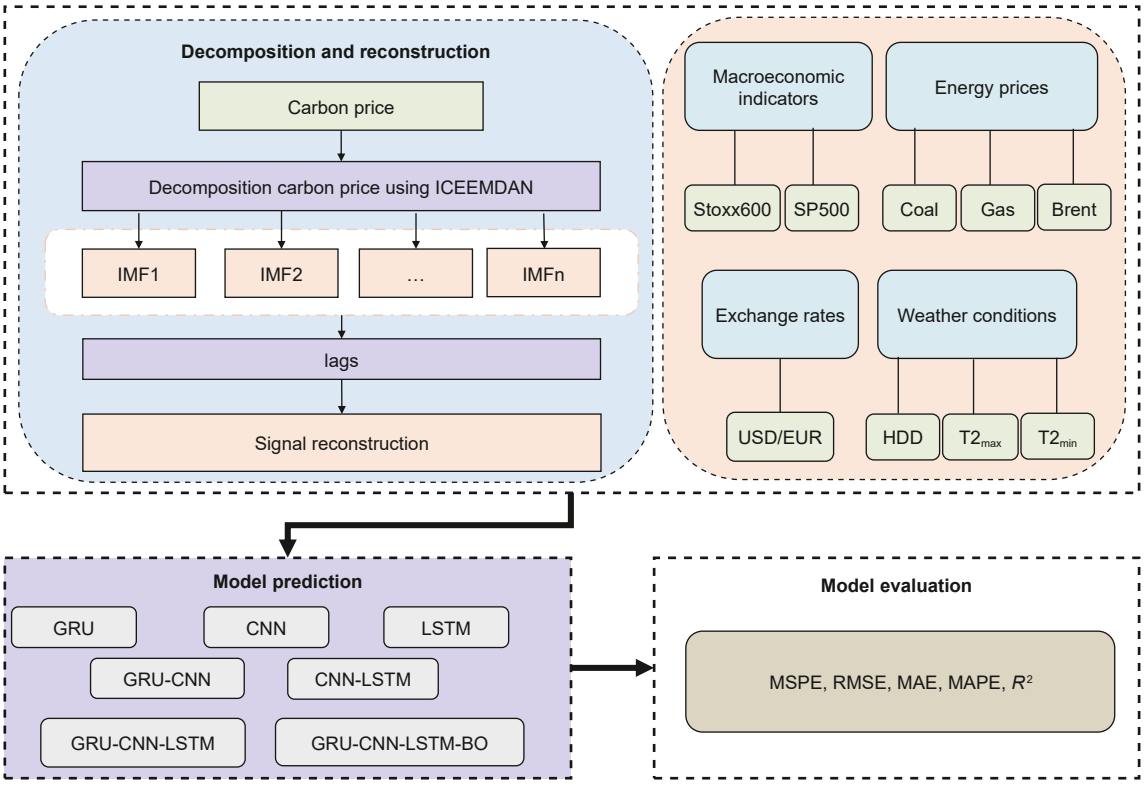

Fig. 1. The main framework of this study. Stoxx600: European stoxx 600 index, SP500: Standard & Poor's 500 index, USD/EUR: USD/EUR exchange rate, Brent: Brent crude oil futures prices, Coal: Coal futures prices, GAS: Natural gas futures prices, HDD: Heating degree day index, $T2_{max}$: Maximum temperature, $T2_{min}$: Minimum temperature, ICEEMDAN: improved complete ensemble empirical mode decomposition with adaptive noise, GRU: gated recurrent unit, CNN: convolutional neural network, LSTM: long short-term memory neural network, BO: Bayesian optimization, MSPE: mean squared percentage error, RMSE: root mean square error, MAE: mean absolute error, MAPE: mean absolute percentage error, R^2: coefficient of determination.

Table 1
Evaluation indicators of this study.

Indicators	Definition	Formula
MAE	Mean absolute error	$\mathrm{MAE} = \frac{1}{T}\sum_{i=1}^{T}\lvert y_i - \hat{y}_i\rvert$
MAPE	Mean absolute percentage error	$\mathrm{MAPE} = \frac{1}{T}\sum_{i=1}^{T}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$
RMSE	Root mean square error	$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(y_i - \hat{y}_i)^2}$
MSPE	Mean squared percentage error	$\mathrm{MSPE} = \frac{1}{T}\sum_{i=1}^{T}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2$
R^2	Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=1}^{T}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{T}(y_i - \bar{y}_i)^2}$

2.2. Factors influencing carbon prices

Carbon prices are impacted by several factors. This study builds indicators of carbon price influencing factors from four aspects: macroeconomic indicators, energy prices, exchange rates and weather conditions (Chen and Zhao, 2024; Feng et al., 2023; Wang et al., 2023; Zhang et al., 2024b).

Macroeconomic indicators: The macroeconomy plays a pivotal role in shaping the dynamics of the carbon market (Mao and Yu, 2024). For instance, high levels of the European stoxx 600 index, which reflects the economic trend of the EU and covers most of the enterprises from public utilities, energy, telecommunication, food, chemicals and other industries in 18 countries of the EU, indicate a booming economy (Zhou and Li, 2019). This leads to higher demand for carbon allowances and, consequently, an upward trend in carbon prices. Similarly, the S&P 500 index, as a leading international market indicator, indirectly influences carbon prices through its impact on energy consumption and production (Zhang et al., 2024b).

Energy prices: Energy consumption is one of the primary sources of carbon emissions, making energy prices a critical factor in carbon price dynamics (Xie et al., 2022). Empirical studies have consistently identified crude oil, natural gas, and coal prices as key indicators shaping carbon price trends (Chevallier et al., 2019; Zhao et al., 2018). Incorporating energy prices such as natural gas futures prices, Brent crude oil futures prices, and coal futures prices into forecasting models is essential for analyzing carbon price fluctuations (Tan and Wang, 2017).

Exchange rates: Exchange rates are widely regarded as a critical factor influencing carbon prices (Sun and Wang, 2020). The exchange rate between the United States dollar and the euro (USD/EUR) serves as a key indicator of international trade competitiveness and cross-border investment flows. For example, a stronger euro relative to the USD reduces the competitiveness of EU exports, potentially dampening industrial activity, energy consumption, and, consequently, the demand for carbon credits, which affects carbon prices (Yu and Mallory, 2014).

Weather conditions: Global warming is becoming increasingly severe with greenhouse gas emissions and CO_2 is identified as the primary contributors to this issue (Dimitriadis et al., 2021). Recent studies highlight that climate change alters energy consumption patterns, influencing fluctuations in carbon prices (Han et al., 2019). The heating degree day index (HDD), published by EUROSTAT, measures the energy required for heating buildings and serves as a critical weather-based indicator. Heating demand for buildings heavily depends on fossil fuels like coal and natural gas, indirectly affecting carbon emissions and increasing the demand for carbon allowances (Uludağ and Tunç, 2020). Thus, incorporating weather-related indices is essential for accurately predicting carbon prices (Qin et al., 2020).

2.3. Decomposition method

The improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) was developed by Colominas et al. (2014) based on the complete ensemble empirical mode decomposition (CEEMDAN). Different from CEEMDAN, ICEEMDAN does not directly add white Gaussian noise $w^{(i)}$ during the decomposition process but selects the k-th intrinsic mode function (IMF) component of the white noise after it has been EMD for decomposition. This approach allows ICEEMDAN to achieve more accurate mode separation with reduced residual noise. The prediction results of the original data series x after ICEEMDAN decomposition are much better than those based on EMD and ensemble empirical mode decomposition (EEMD), providing room for improvement in carbon price prediction (Hao and Tian, 2020).

The ICEEMDAN operates through an iterative process. At each iteration k, $w^{(i)}$ is first decomposed using EMD, and the k-th IMF $E_k\left(w^{(i)}\right)$ is extracted. These IMF components are scaled and added to the current residual r_k to form an ensemble of perturbed signals. Each of these signals is then decomposed by EMD to extract the first IMF, and the resulting IMFs are averaged across the ensemble to obtain the mode $\tilde{m}_k$. This mode is subtracted from the current residual to produce r_{k-1}, and the process repeats. The decomposition terminates when the residual becomes monotonic or a predefined maximum number of IMFs is reached.

2.4. Main forecasting models

2.4.1. GRU model

Gated recurrent unit (GRU), proposed by Cho et al. (2014), is an improved recurrent neural network (RNN) specialized in dealing with long term dependencies in sequential data. GRU simplifies the RNN structure by using two gates: a reset gate r_t and an update gate u_t, which regulate information flow and help mitigate gradient vanishing and explosion problems.

GRU is used as the initial layer to model short-term temporal dependencies efficiently. For each time step t, the hidden state h_t is updated as:

$$h_t = (1 - u_t)h_{t-1} + u_t\tilde{h}_t \tag{1}$$

where $\tilde{h}_t$ denotes the intermediate hidden state.

2.4.2. CNN model

Convolutional neural network (CNN), though originally developed for image recognition, has been successfully adapted to time series forecasting. As demonstrated by Borovykh et al. (2017), CNN can apply 1D convolutions along the temporal axis to extract localized patterns and short-term dependencies. In this study, a 1D convolution layer is applied to extract spatial features across feature channels over time. The output of the i-th feature map in the $(n+1)$-th layer at time step τ is defined as:

$$y_i^{(n+1)}(\tau) = \delta\left(x_i^n + \sum_{f=1}^{F^n} K_{fi}^n \times y_f^n(\tau)\right) \tag{2}$$

where $y_i^{(n+1)}(\tau)$ denotes the feature map i in the $n+1$ layer. δ represents the number of feature maps in n layers. K_{fi}^n denotes the kernel in layer n that operates on the feature map f to create feature map i in layer $n+1$. x_i^n denotes the deviation vector.

2.4.3. LSTM model

Long short-term memory (LSTM) was introduced by Hochreiter and Schmidhuber (1997) to overcome the vanishing gradient problem in recurrent neural networks. By using a memory cell along with input, output, and forget gates, LSTM can retain long-term dependencies, making it widely used in sequential learning tasks. It is especially applicable to long, noisy time series with delayed effects, such as policy-driven market behavior. The internal structure of LSTM unit is shown in Fig. 2. The internal memory cell c_t and hidden state h_t are updated as:

$$c_t = f_t \times c_{t-1} + i_t \times \tilde{c}_t \tag{3}$$

$$h_t = o_t \times \tanh(c_t) \tag{4}$$

where the f_t, i_t, $\tilde{c}_t$, and o_t denote the forget gate, the input gate, the candidate memory cell, and the output gate respectively.

2.5. Hyperparameter optimization

Bayesian optimization (BO) is a black-box optimization method based on Bayesian probabilistic inference and is commonly used for hyperparameter tuning in machine learning models. Wang et al. (2024) demonstrated the effectiveness of BO in optimizing the hyperparameters of complex models.

The theoretical framework of the BO algorithm basically consists of three steps:

Step 1 Selecting the next most "promising" evaluation point x based on the maximization of the acquisition function.
Step 2 Evaluating the objective function value $y = f(x) + \in_i$ based on the selected evaluation point x.

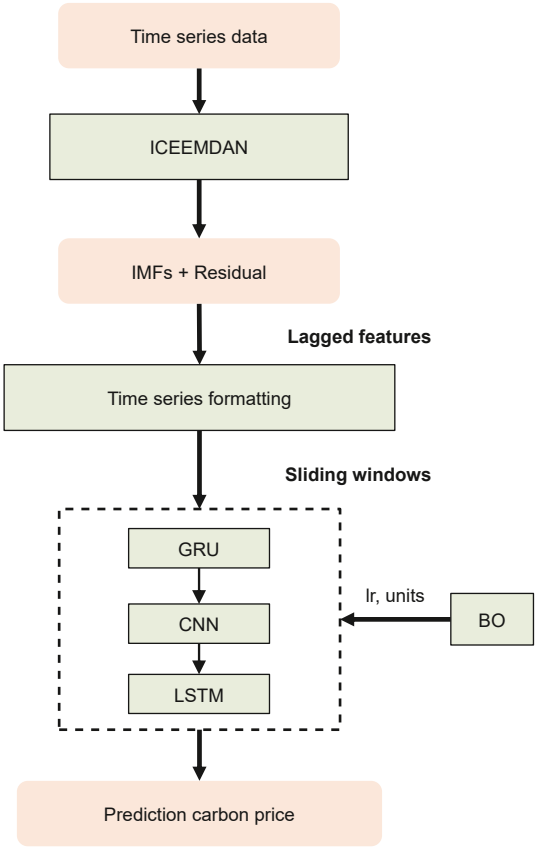

Fig. 3. Workflow of the proposed hybrid forecasting framework.

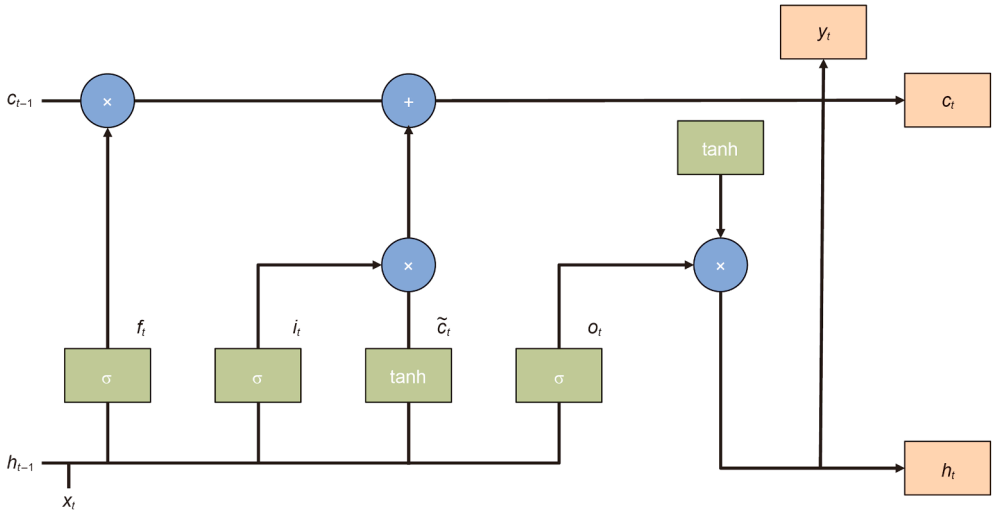

Fig. 2. The internal structure of long short-term memory unit.

Step 3 Pairing the newly obtained input observation pairs $\{x_i, y_i\}$ into the historical observation set D_{i-1}, and updating the probabilistic agent model for the next iteration.

2.6. Hybrid framework

The overall structure of the proposed hybrid forecasting framework is illustrated in Fig. 3. The workflow and interactions among the components are as follows.

ICEEMDAN decomposition: The process begins by applying ICEEMDAN to the original carbon price time series to extract decomposed IMFs and a residual. Rather than modeling each IMF independently, ICEEMDAN is employed as a data preprocessing method to capture the multi-frequency characteristics of the signal while reducing noise. The resulting components are then transformed into lagged features and combined with external variables to construct a comprehensive feature matrix for unified model training.

Hybrid deep learning module: The GRU, CNN, and LSTM layers are connected sequentially to enable hierarchical learning of spatial-temporal representations. The GRU layer captures short-term dependencies with fewer parameters, enhancing training efficiency (Wang et al., 2021). The CNN layer extracts local spatial patterns and fluctuations within the input sequence (Huang et al., 2022). The LSTM layer models long-term sequence trends and contextual memory, allowing the network to capture both short-term variations and long-range dynamics effectively (Shi et al., 2024).

BO: To enhance robustness and reduce manual parameter tuning, BO is applied to optimize the architecture's hyper-parameters. These include the number of hidden units in each layer and learning rate. BO searches the hyperparameter space using probabilistic modeling to improve generalization and performance across datasets.

3. Data collection and description

3.1. Data sources

This study constructs a system of influencing factors for EUA futures prices, with data sources detailed in Table 2, which may also serve as a reference for similar studies in other countries and regions.

The carbon price data (closing price) of EU ETS are obtained from the Intercontinental Exchange (ICE) (https://sc.macromicro.me/series/17456/ice-eua-futures), as shown in Fig. 4. The selected time nodes for each variable are from January 1, 2018 to November 30, 2023, and excluding non-trading day data, the dataset includes 1545 samples. Missing values are filled in using the linear interpolation. For model training purposes, the dataset is divided into training and test sets in a ratio of 8:2.

3.2. Data pre-processing

Table 3 presents descriptive statistics for each indicator. The carbon price (CPrice) of EU ETS averages 47.84 €/tCO_2, with a minimum of 8.07 €/tCO_2, a maximum of 98.01 €/tCO_2, and a standard deviation of 28.02, reflecting notable volatility. These statistical features suggest the existence of nonlinear dynamics, asymmetrical behaviors, and potential interrelationships among the variables, thereby necessitating the use of more adaptable and sophisticated modeling techniques.

The original data of external influencing factors have different magnitudes and units. It is crucial to preprocess the data by scaling it to the range [0, 1] to ensure consistency across variable scales and eliminate the impact of scale differences on the model (Tian et al., 2024), as shown in Eq. (5).

$$Z^* = \frac{Z - Z_{\min}}{Z_{\max} - Z_{\min}} \tag{5}$$

where Z^* represents the normalized value of the data; Z is the input data, and $Z_{\min}$ and $Z_{\max}$ represent the minimum and maximum values of the input data, respectively.

The augmented dickey-fuller (ADF) test, proposed by Dickey and Fuller (1979), is a statistical method used to determine whether time series data has a unit root, which helps assess whether the data is stationary (Feng et al., 2023). The ADF test for the historical carbon price data of the EU ETS yields a p-value of 0.6877, which is greater than the commonly chosen significance levels (e.g., 0.05 or 0.01). Therefore, traditional econometric methods are unsuitable for analyzing this data. Instead, an integrated learning approach is adopted to predict the non-stationary time series of carbon prices.

To examine the relationship between historical carbon price variables and current carbon price data, this study employs the partial autocorrelation function (PACF) to identify key input features for prediction. As shown in Fig. 5, the PACF results indicate that the first lag is significant. It suggests that the carbon price in the previous period has a substantial direct impact on the current price and serves as a primary driver in the EU ETS. Therefore, the first lag is included in the models.

4. Experiments and results analysis

All forecasting models in this study were developed and executed through Python 3.12. To capture temporal dependencies, a sliding time window strategy is employed, where the model takes the past five-time steps to predict the next one. This setup effectively integrates multiscale signal components and external influences within a unified sequence learning framework,

Table 2
External influencing factors for European Union allowance future prices.

Dimension	Factor	Variable	Data source
Macroeconomic indicators	European stoxx 600 index	Stoxx600	https://cn.Investing.com
	Standard & Poor's 500 index	SP500	https://cn.Investing.com
Energy prices	Natural gas futures prices	Gas	https://cn.Investing.com
	Brent crude oil futures prices	Brent	https://cn.Investing.com
	Coal futures prices	Coal	https://cn.Investing.com
Exchange rates	USD/EUR exchange rates	USD/EUR	https://cn.Investing.com
Weather conditions	Heating degree day index	HDD	https://cds.climate.copernicus.eu
	Maximum temperature	$T2_{max}$	https://cds.climate.copernicus.eu
	Minimum temperature	$T2_{min}$	https://cds.climate.copernicus.eu

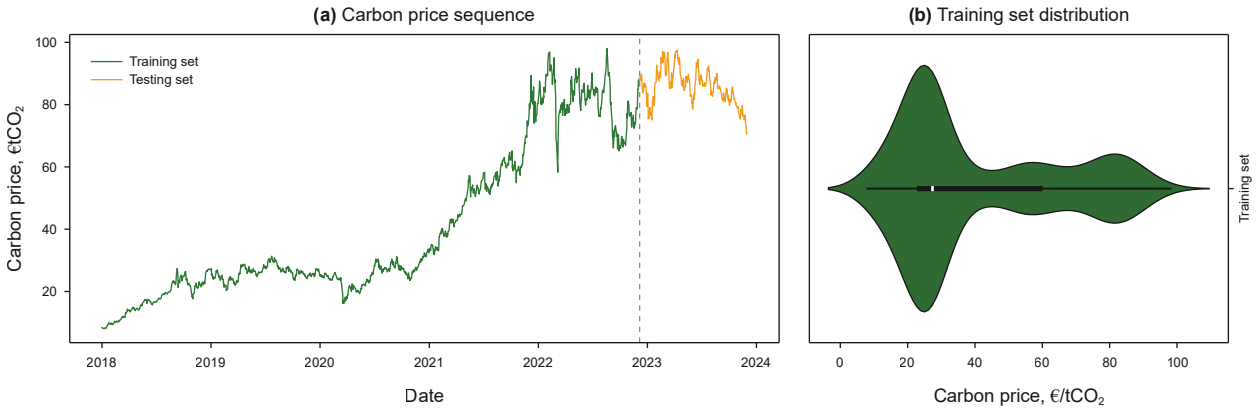

Fig. 4. Carbon price data of European Union emissions trading system.

Table 3
Descriptive statistics of carbon price data and external variables.

Indicator	Mean	Std	Min	25%	50%	75%	Max
CPrice	47.84	28.02	8.07	24.57	31.62	79.31	98.01
Stoxx600	411.04	41.80	279.66	378.42	407.35	451.76	494.35
SP500	3573.16	684.23	2237.40	2887.00	3662.40	4188.40	4796.60
Gas	3.51	1.70	1.54	2.56	2.85	3.79	9.65
Brent	71.76	18.93	19.33	61.82	72.18	82.87	127.98
Coal	123.52	88.48	38.60	59.33	95.25	138.75	438.35
USD/EUR	0.89	0.048	0.80	0.85	0.89	0.92	1.04
HDD	195.30	144.09	11.52	38.44	165.91	325.70	468.05
$T2_{max}$	287.68	7.34	275.56	281.39	287.55	295.05	298.81
$T2_{min}$	280.41	5.91	270.39	274.99	280.17	286.71	289.49

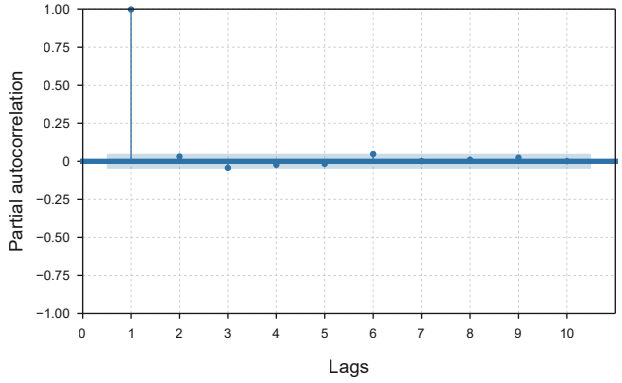

Fig. 5. The partial autocorrelation function result analysis.

enhancing both predictive accuracy and interpretability. For the benchmark models, the GRU model was configured with 128 units, the CNN model utilized 128 convolutional filters with a kernel size of 3, and the LSTM model comprised 64 units. Model training was performed with a batch size of 32 and an initial learning rate of 0.001. To mitigate overfitting, dropout rates of 0.2, 0.3, and 0.4 were applied to different layers depending on the model architecture. Furthermore, BO was employed to fine-tune key hyperparameters. The optimization was conducted within the parameter bounds {'lr': (1e−4, 1e−2), 'units': (64, 256)}, targeting the learning rate and the number of units in recurrent layers.

4.1. ICEEMDAN decomposition of carbon prices

The number of IMFs extracted by ICEEMDAN was determined through a sensitivity analysis. Detailed results are presented in

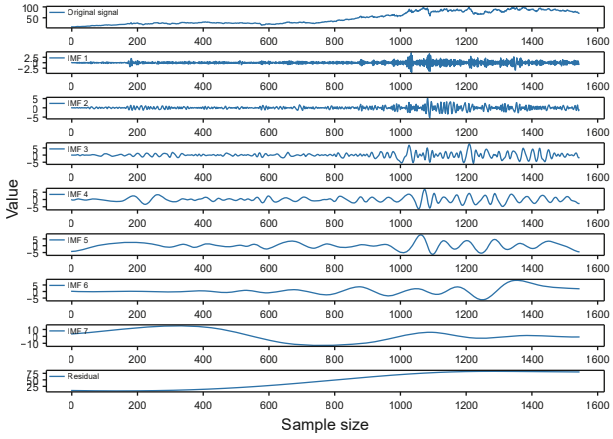

Fig. 6. Decomposition results from improved complete ensemble empirical mode decomposition with adaptive noise.

Appendix B. The parameter max_imfs was varied from 5 to 8 to assess the decomposition quality and model performance. Extracting more than 7 components yielded IMFs with low amplitude and limited interpretability, while the residual became negligible and close to zero. This indicates potential over-decomposition and redundancy. Conversely, limiting the number of IMFs to 5 or 6 resulted in the loss of meaningful temporal structures. Therefore, max_imfs = 7 was adopted to balance decomposition granularity and signal interpretability.

As shown in Fig. 6, the carbon price data are decomposed using the ICEEMDAN, which decomposes the carbon price series into seven IMFs and one residual component. Based on the Hilbert mean frequency, the high-frequency (IMF 1–2), with average frequencies of 0.32 and 0.13, represent short-term price variability, often driven by immediate factors such as abrupt policy changes, energy price volatility, and market disturbances. The mid-frequency (IMF 3–4), with average frequencies of 0.05 and 0.02, reflects the cyclical patterns in the carbon market, and is associated with factors such as quarterly supply and demand shifts, and seasonal adjustments in the EU ETS emission allowances. The low-frequency (IMF 5–7), progressively lower frequencies below 0.001, represent slower, more persistent trends linked to structural changes in the market (Zhang et al., 2008). The residual component has an average frequency of 0.00, reflecting the long-term trend. Collectively, these decomposed components illustrate the multi-scale nature of carbon price dynamics in the EU carbon

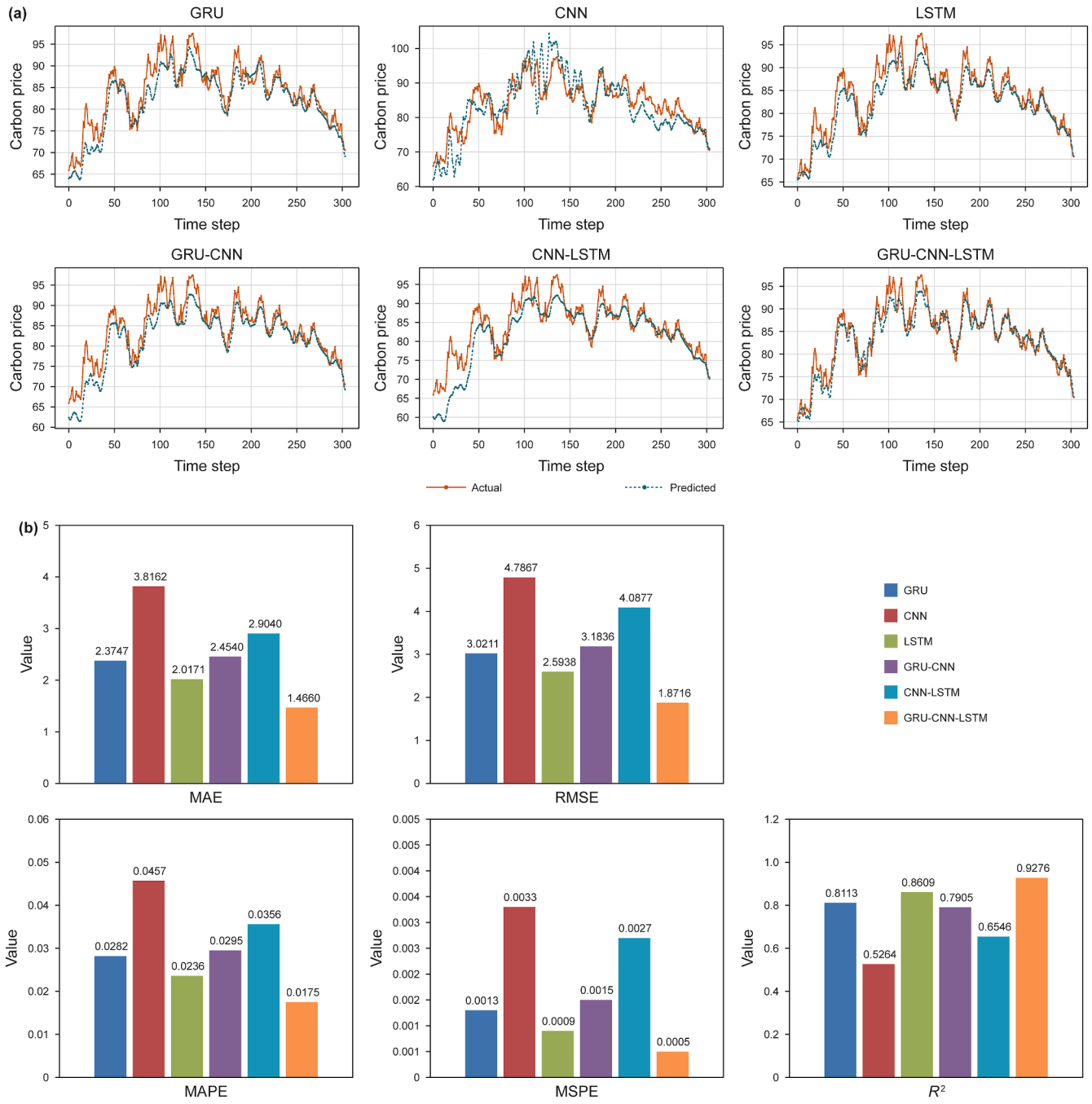

Fig. 7. **(a)** Comparison of carbon price forecasting performance across different models; **(b)** comparison of evaluation metrics.

market. It shows the combined effects of short-term fluctuations and long-term trends driven by a complex interplay of economic, policy, and environmental factors.

4.2. Model prediction and evaluation

Fig. 7(a) presents the forecasting results of each model. Intuitively, among the single models, LSTM performs better than GRU, and GRU outperforms CNN, indicating that recurrent neural networks capture temporal patterns more effectively than pure convolutional structures. For all models, the hybrid GRU-CNN-LSTM model predictions align more closely with the actual carbon price trends, whereas the benchmark models demonstrate certain limitations in predictive accuracy, particularly during periods of intense fluctuations. Fig. 7(b) provides a quantitative comparison of forecasting performance. The GRU-CNN-LSTM model consistently demonstrates superior predictive performance compared to the benchmark models. Notably, the GRU-CNN-LSTM model achieves the best performance across all evaluation metrics, with the lowest MAE (1.4660), RMSE (1.8716), MAPE (0.0175), and MSPE (0.0005), along with the highest R^2 (0.9276). Compared to all benchmark models, the GRU-CNN-LSTM model achieves reductions in MAE and RMSE ranging from 27.32% to 61.58% and 27.84% to 60.90%, respectively. These results clearly indicate that

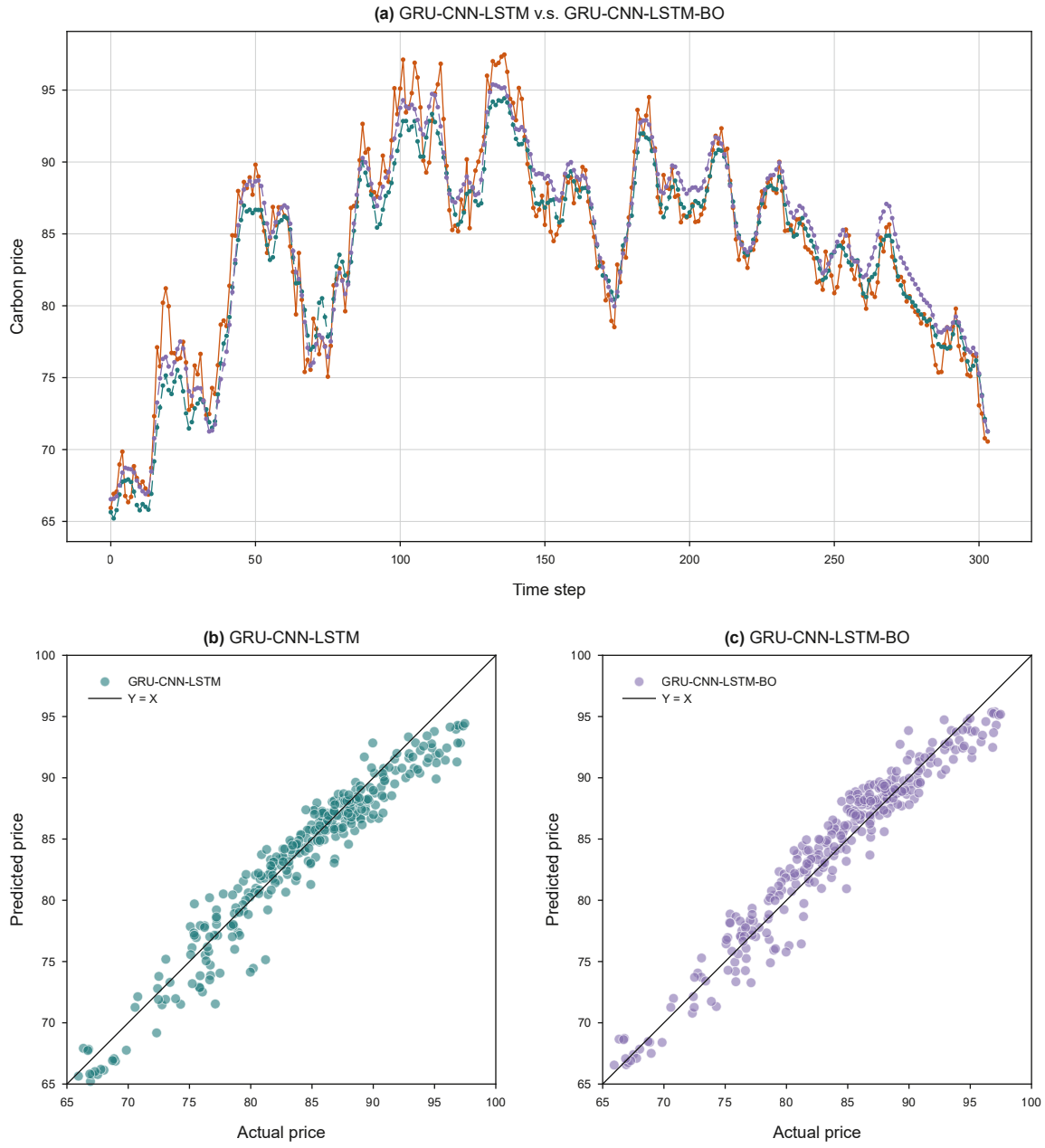

Fig. 8. Comparison of carbon price forecasting before and after Bayesian optimization.

the hybrid framework enables the model to more effectively capture critical features and relationships within the data, thereby significantly enhancing predictive accuracy and model fitting.

4.3. GRU-CNN-LSTM model based on BO

To further improve the predictive accuracy of the GRU-CNN-LSTM model, BO is applied to fine-tune critical hyperparameters (Hao and Tian, 2020). As shown in Fig. 8(a), although the unoptimized GRU-CNN-LSTM model is capable of capturing the overall carbon price trends, it exhibits noticeable deviations at critical peak and trough regions, such as within the 50–150 time step interval. The optimized model shows a much closer alignment with the actual values. Fig. 8(b) and (c) further validate these findings through scatter plot comparisons. The GRU-CNN-LSTM-BO model exhibits a tighter clustering of predicted values around the 45-degree reference line, reflecting higher consistency with actual prices and reduced dispersion compared to the unoptimized model.

Fig. 9 provides a comprehensive comparison of forecasting performance between GRU-CNN-LSTM and GRU-CNN-LSTM-BO. The evaluation metrics consistently indicate that incorporating BO enhances the predictive accuracy and robustness. The GRU-CNN-LSTM-BO model outperforms the GRU-CNN-LSTM in all the indexes, achieving lower MAE (1.3872), RMSE (1.7038), MAPE (0.0166), and MSPE (0.0004), with reductions of 5.38%, 8.97%, 5.14%, and 20%, respectively. At the same time, the R^2 increases by 1.34%, from 0.9276 to 0.9400, indicating improved model fit. These results demonstrate that BO significantly enhances the GRU-CNN-LSTM model's ability to capture the complex and dynamic characteristics of carbon price movements, while preserving the strengths of its original architecture. Compared to all benchmark

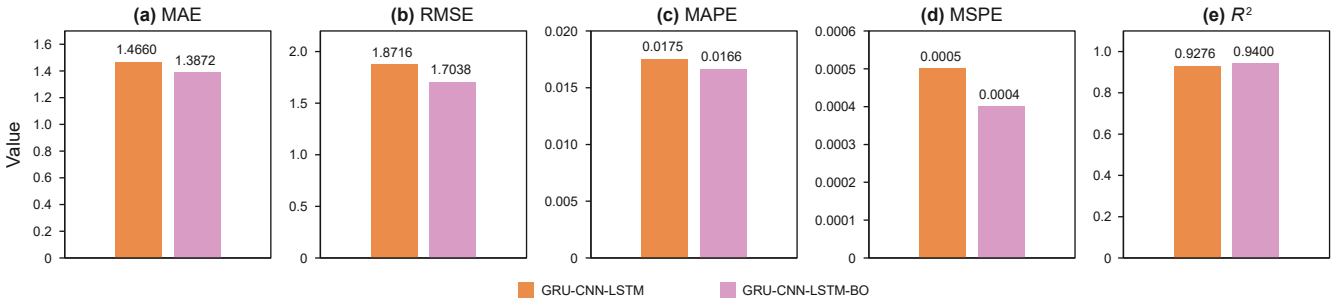

Fig. 9. Comparison of evaluation indicators between GRU-CNN-LSTM and GRU-CNN-LSTM-BO.

models, the GRU-CNN-LSTM-BO model achieves reductions in MAE and RMSE ranging from 5.38% to 63.65% and 8.97%–64.41%, respectively. This improved predictive performance provides more accurate and timely decision support for carbon market participants, enabling them to better navigate market volatility and implement effective trading or policy strategies.

4.4. Discussion

Carbon price fluctuations directly affect the economic viability of low-carbon technology projects. As China advances toward its carbon neutrality goals, carbon prices are expected to rise steadily (Ma et al., 2025). This makes accurate forecasting of China's carbon market prices essential for policy formulation, investment decisions, and project operations. To further validate the applicability of the proposed framework for forecasting carbon prices influenced by external factors, the China's national ETS prices are selected as an additional dataset for simulation. The carbon price data (closing price) of China's national ETS are obtained from the official carbon trading platform of China (http://wwwtanjiaoyi.com/). The dataset spans from July 16, 2021 to May 13, 2024, as shown in Fig. 10. External influencing factors incorporate macroeconomic indicators (Shanghai composite index, Shanghai-Shenzhen 300 index, Standard & Poor's 500 index, Dow Jones industrial average) (Mao and Yu, 2024; Pham et al., 2019; Zhang et al., 2024b), energy prices (natural gas futures prices, Brent crude oil futures prices, coal futures prices) (Chevallier et al., 2019; Tan and Wang, 2017; Xie et al., 2022; Zhao et al., 2018), and international carbon prices (EUA futures prices) (Ji et al., 2019), sourced from Yingwei Finance (https://cn.Investing.com) and ICE (https://sc.macromicro.me/series/17456/ice-eua-futures). The experimental methodology and procedures for this dataset remain consistent with those previously applied. To avoid redundancy, this section solely outlines the results without delving into detailed analyses. Descriptive statistics of the China's ETS dataset are provided in Appendix A.

Fig. 11(a) illustrates the comparison between actual carbon prices and predicted values for each model. Among all the models, the GRU-CNN-LSTM-BO demonstrates the closest alignment with the actual price series, capturing both the overall upward trend and local fluctuations with higher accuracy. Notably, the unoptimized GRU-CNN-LSTM model, while outperforming most benchmarks, exhibits some lag in response to sharp price changes, which is significantly mitigated after BO. As shown in Fig. 11(b), the results clearly demonstrate the superior predictive capability of the proposed GRU-CNN-LSTM-BO model. Initially, the GRU-CNN-LSTM model achieved MAE, RMSE, MAPE, and MSPE values of 3.6238, 4.0028, 0.0438, and 0.0023, respectively, along with an R^2 value of 0.8524. Following hyperparameter tuning through BO, the model's performance improved significantly, with the GRU-CNN-LSTM-BO attaining lower error metrics: MAE reduced to 1.9492, RMSE to 2.5307, MAPE to 0.0231, and MSPE to 0.0008, while the R^2 value increased to 0.9410. Compared to all benchmark models, the GRU-CNN-LSTM model achieves reductions in MAE and RMSE ranging from 46.21% to 62.05% and 36.78% to 70.88%, respectively.

A further comparative analysis reveals that the GRU-CNN-LSTM-BO model achieves similar R^2 in both the EU ETS and China's national carbon market, 0.9400 and 0.9410, respectively, indicating strong fitting capabilities in both markets. However, the prediction errors in China's national carbon market are significantly higher than those in the EU ETS. Specifically, the MAE and RMSE in China's national carbon market increased by 40.51% and 48.53%, respectively, compared to those in the EU ETS, which reflects the higher volatility and greater instability inherent in

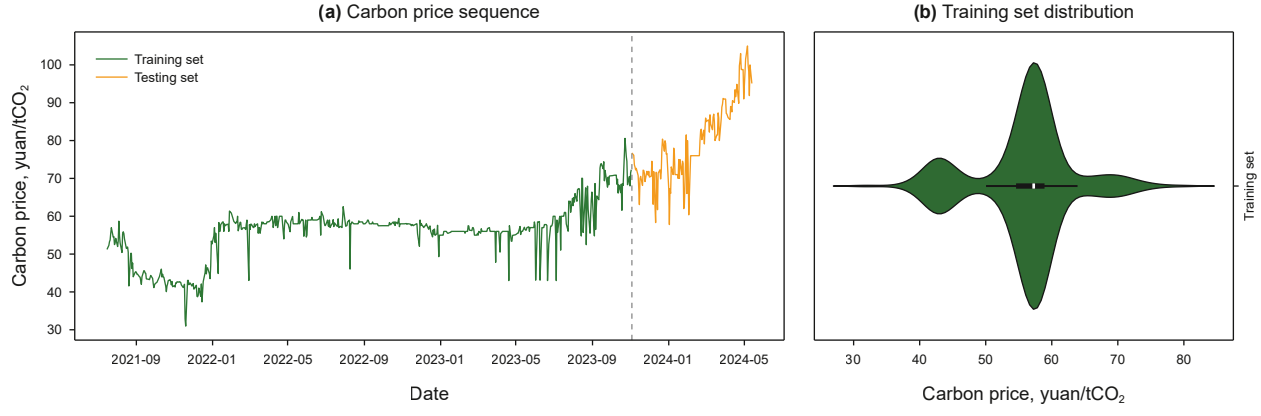

Fig. 10. Carbon price data of China's national emission trading scheme.

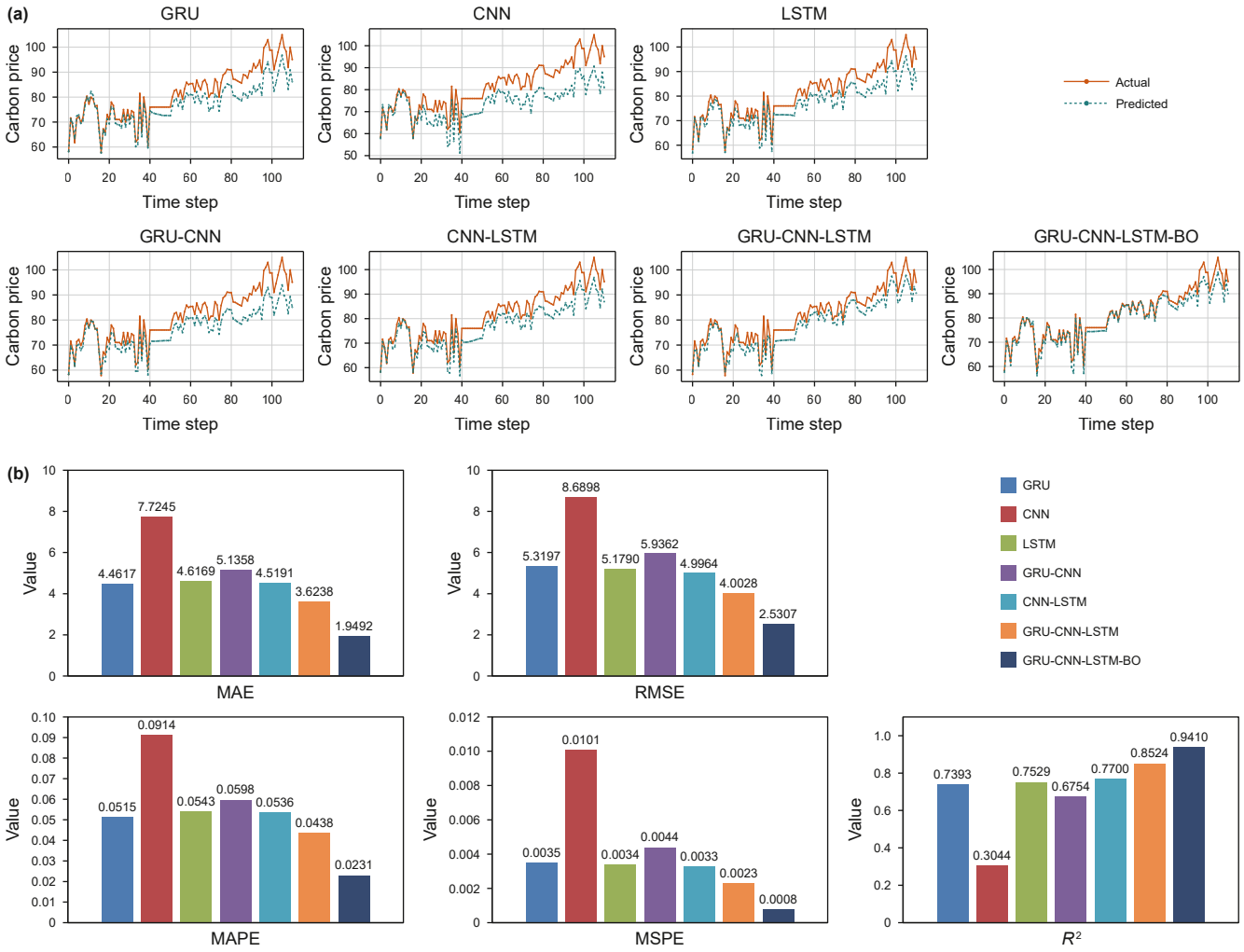

Fig. 11. **(a)** Comparison of forecasting carbon prices by different models based on China's carbon market prices; **(b)** comparison of evaluation indicators based on China's carbon market prices forecasting.

China's carbon market. Moreover, when comparing the performance improvements of the hybrid framework over benchmark models, it becomes evident that China's carbon market benefits more significantly from the introduction of the hybrid framework. In the EU ETS, the GRU-CNN-LSTM-BO model reduces MAE and RMSE by an average of 39.59% and 42.68%, respectively. In contrast, the reductions in MAE and RMSE for China's carbon market range by an average of 59% and 52.98%, respectively. This indicates that while China's market presents greater forecasting challenges due to higher volatility, the ensemble model demonstrates superior adaptability in such complex environments, effectively mitigating the limitations of single models in capturing sharp market fluctuations.

Overall, the experimental results confirm the robustness and adaptability of the proposed framework, which integrates signal decomposition with a hybrid GRU-CNN-LSTM-BO model for carbon price forecasting. The framework proves to be a reliable and flexible tool, offering actionable insights for carbon market participants and policymakers across diverse regional contexts.

5. Conclusion

This study proposes an efficient and adaptive framework for predicting carbon prices by focusing on the complex, nonlinear, and multi-scale nature of carbon market dynamics. An empirical study of the EU ETS is conducted using a hybrid GRU-CNN-LSTM-BO framework, enhanced by ICEEMDAN. The performance of the proposed framework is systematically evaluated across five key metrics, demonstrating that the hybrid framework significantly outperforms benchmark models. Furthermore, to validate the applicability and robustness of the proposed framework, an additional empirical study is conducted using the China's national carbon market data. The results further confirm its generalizability and adaptability to diverse ETS, highlighting its potential for broader application in global carbon markets. The main findings of this study are as follows:

(1) The proposed forecasting framework, which integrates ICEEMDAN decomposition and a hybrid GRU-CNN-LSTM model, proves to be highly effective in improving carbon price prediction accuracy. Compared to all benchmark models, the GRU-CNN-LSTM model achieves reductions in MAE and RMSE ranging from 27.32% to 61.58% and 27.84% to 60.90% respectively in the EU ETS. The hybrid GRU-CNN-LSTM framework strengthens forecasting capability by combining the strengths of each architecture: GRU for efficient long-term dependency modeling, CNN for short-term pattern recognition, and LSTM for capturing nonlinear

sequential dynamics. This synergy enables the model to better handle both smooth trends and abrupt market fluctuations.

(2) Beyond architectural improvements, the incorporation of BO significantly enhances the model's robustness and accuracy. By systematically tuning hyperparameters such as learning rate and layer dimensions, BO prevents underfitting or overfitting and improves the model's ability to adapt to complex, nonlinear changes in carbon price dynamics. Empirical results show that the GRU-CNN-LSTM-BO model outperforms the GRU-CNN-LSTM in all the indexes, achieving lower MAE (1.3872), RMSE (1.7038), MAPE (0.0166), and MSPE (0.0004), with reductions of 5.38%, 8.97%, 5.14%, and 20%, respectively.

(3) Empirical results demonstrate that the proposed framework achieves higher predictive accuracy in the EU ETS compared to China's national carbon market. Specifically, the GRU-CNN-LSTM-BO achieves an MAE of 1.3872, RMSE of 1.7038, MAPE of 0.0166, and MSPE of 0.0004, whereas in China's national carbon market, these values increased to 1.9492, 2.5307, 0.0321, and 0.0008, respectively. This indicates that, despite the model's enhanced adaptability, China's carbon market remains more challenging to predict due to inherent market characteristics. This superior performance in the EU ETS can be attributed to the market's maturity, more stable price dynamics, and the comprehensive inclusion of relevant external factors. In contrast, China's carbon market is still in an early developmental phase, currently restricted to the power generation sector, with evolving regulatory mechanisms and frequent policy interventions. Additionally, its smaller market scale and greater exposure to non-rational price fluctuations contribute to heightened volatility, thereby posing significant challenges for accurate predictive modeling.

The proposed hybrid framework in this study is not only effective for improving predictive accuracy, but also well-suited for downstream applications across the energy sector. In the refining sector, anticipated carbon cost trajectories can inform feedstock procurement and product pricing strategies, especially under emissions trading obligations or border adjustment mechanisms. In electricity markets, carbon price signals shape dispatch decisions and the planning of emission allowance acquisitions, contributing to more cost-effective and lower-carbon operations. For carbon asset managers, reliable forecasts support more strategic timing of emissions trading decisions, improving cost control and mitigating exposure to market volatility. The proposed framework also serves as a tractable simulation tool for regulators to evaluate the implications of alternative carbon pricing scenarios and design more responsive climate interventions in dynamic market contexts.

Building on the promising results of this study, several opportunities for future research are evident, particularly in the context of enhancing carbon price forecasting in China's carbon market. First, the model could be extended to include a broader set of external influencing factors, such as climate variables, policy uncertainty indicators, global economic shocks, or technological advancements in energy sectors, to improve its robustness and adaptability to evolving market conditions. Second, exploring alternative optimization algorithms and advanced decomposition techniques could further enhance prediction accuracy and computational efficiency. Third, the model's ability to process nonlinear and highly volatile data should be strengthened, with the introduction of attention-based deep learning models such as Transformers to capture complex dynamic features more effectively. Finally, expanding the model to more other carbon markets could further validate the model's generalizability. By addressing these aspects, future research can contribute to the development of more comprehensive, flexible, and scalable forecasting frameworks, supporting policy-making and investment decisions in the increasingly complex global carbon market.

CRediT authorship contribution statement

Hao-Zhen Li: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Tian-Ming Shao:** Writing – original draft, Supervision, Methodology, Data curation, Conceptualization. **Xin Gao:** Writing – review & editing, Visualization, Validation, Formal analysis. **Feng Gao:** Writing – review & editing, Methodology, Funding acquisition, Data curation. **Arash Farnoosh:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowlegements

This study was supported by the National Natural Science Foundation of China (Grant No. 72401011).

Appendix A

Table A1
Descriptive statistics of China's ETS carbon price dataset.

Indicator	Mean	Std	Min	25%	50%	75%	Max
CPrice	60.26	12.07	30.97	55.73	58.00	63.86	105.00
Stoxx600	3232.95	208.67	2702.19	3074.02	3223.53	3350.11	3715.37
HS300	4078.04	491.33	3179.63	3727.70	3999.44	4320.60	5151.75
Coal	188.44	90.33	93.25	119.00	141.10	255.53	438.35
Brent	87.41	12.10	65.18	79.03	84.58	92.84	127.98
Gas	4.34	2.10	1.55	2.56	3.76	5.82	9.65
SP500	4354.78	380.58	3577.03	4059.14	4369.01	4566.88	5254.35
EUA	77.34	11.50	51.16	68.13	80.12	86.25	98.01
DJI	34445.19	2195.48	28725.51	33140.03	34212.12	35456.56	39807.37

Appendix B

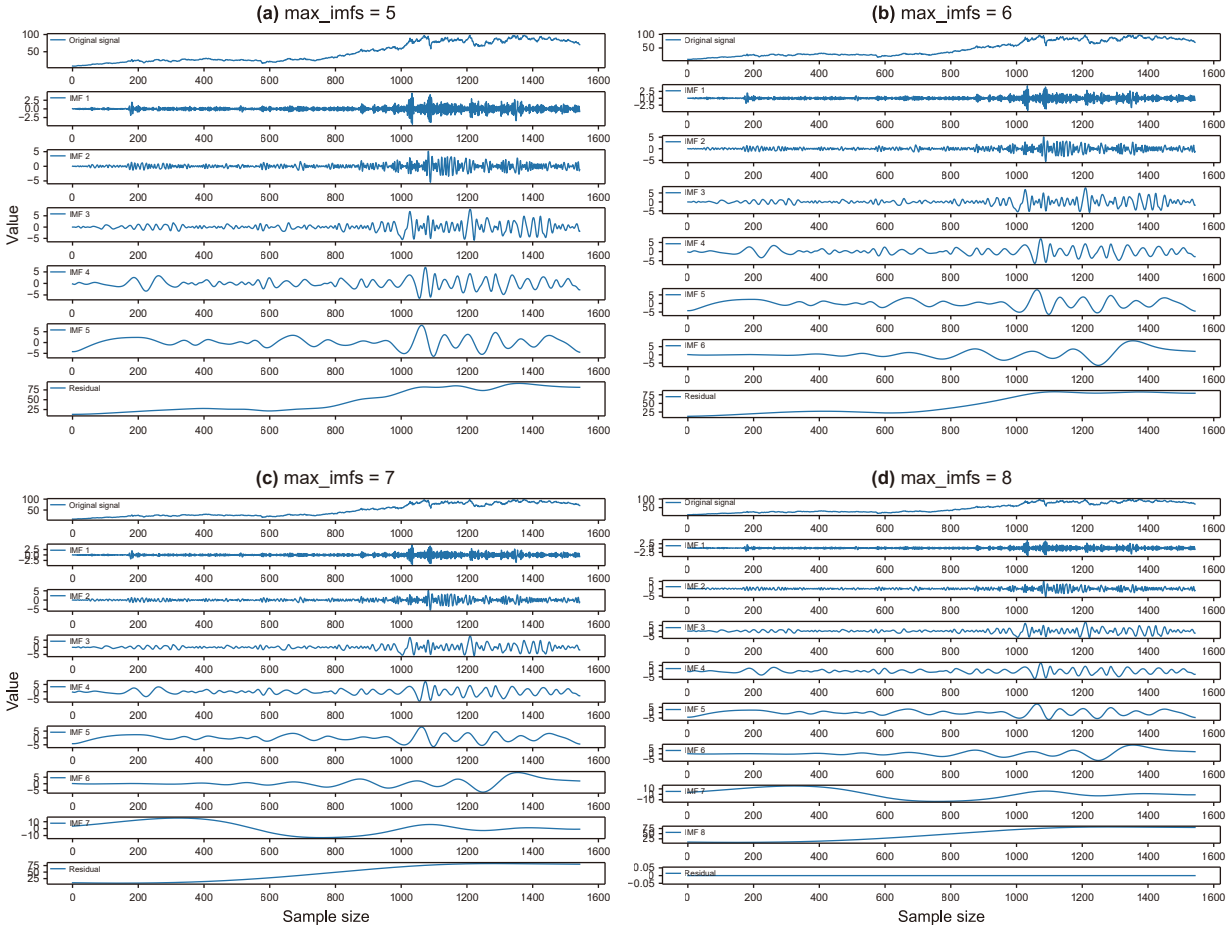

Fig. B1. Sensitivity analysis of the number of extracted IMFs.

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