

ARTICLE

A hybrid convolutional neural network–
bidirectional long short-term memory–attention
framework for carbon price forecasting with
residual error correction

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Abstract

Carbon trading markets are important mechanisms for reducing greenhouse gas emissions; however, carbon prices are highly volatile due to the influence of energy markets, economic conditions, regulatory policies, and investor sentiment. This study proposes a hybrid machine learning and natural language processing (ML–NLP) framework for interval-based carbon price forecasting by integrating structured market indicators with sentiment features extracted from financial news, policy announcements, and market discussions. The proposed model combines convolutional neural networks, bidirectional long short-term memory networks, and an attention mechanism to capture complex temporal dependencies and feature interactions, along with a residual error correction module to improve forecasting accuracy. The framework is evaluated using real-world European Union and China Emission Trading Systems carbon allowance price datasets. The results demonstrate that the proposed approach effectively captures nonlinear carbon market patterns and improves prediction performance, reducing mean absolute error from 2.84 €/tCO₂ to 1.76 €/tCO₂ after residual correction. The findings confirm that integrating deep learning, sentiment analysis, and residual learning provides an effective approach for reliable carbon price forecasting.

Keywords: Convolutional neural networks; Bidirectional long short-term memory networks; Hybrid machine learning; Natural language processing

1. Introduction

Global climate change has become one of the most critical environmental issues in the 21st century. In this regard, most nations have implemented market-driven policies to curb greenhouse gas emissions. Under these mechanisms, carbon trading systems have been seen as one of the most effective policy tools, enabling organizations to trade emission allowances in regulated markets (Y. Yang *et al.*, 2021). Carbon markets offer monetary rewards to industries to reduce their environmental impact, encouraging sustainable development. As carbon trading systems spread globally, precise forecasting of carbon prices has gained particular significance for policymakers, investors, and market participants.

The dynamics of carbon prices are affected by various factors, such as the energy market, macroeconomic indicators, regulatory rules, and social attitudes to environmental problems. Such considerations introduce uncertainty and volatility into carbon markets, making accurate forecasting challenging (W. Sun & Zhang, 2022). Older statistical techniques such as autoregressive and econometric methods have been extensively applied to price prediction, but because they do not recognize nonlinear relationships and compound interactions among various market variables, they are not effective. As artificial intelligence methods become more popular, machine learning (ML) and deep learning models are becoming more applicable to financial forecasting issues due to their ability to learn complex data patterns.

Recent studies have indicated that deep neural networks, especially long short-term memory networks (LSTMs) and recurrent neural networks, are effective in sequential financial data modeling (P. Yang *et al.*, 2023). Nevertheless, numerous carbon price prediction studies do not use unstructured written materials like news articles, government policy announcements, and social media discussions, which are valuable sources of information and are mostly ignored in current studies. These sources of text address business moods and market expectations, which may cause substantial changes in prices in carbon trading markets.

Natural language processing (NLP) techniques entail powerful methods of extracting meaningful information from large amounts of textual data. Sentiment analysis can capture public and investor sentiment, which is a significant driver of market movements (Yun *et al.*, 2023). By combining sentiment features with quantitative financial indicators, it is possible to improve the predictive performance of forecasting models. In addition, carbon markets are highly volatile and uncertain, and interval prediction techniques are more appropriate than traditional

point forecasts, as they offer a range of potential results and more effectively define market uncertainty.

Given these difficulties, this research offers a hybrid ML and NLP model to predict carbon prices at intervals with a value. The suggested system combines structured financial indicators and sentiment-based textual features in a single forecasting pipeline. A hybrid deep learning model consisting of convolutional neural networks (CNNs), bidirectional LSTMs (BiLSTMs), and an attention mechanism is used to reveal the interaction of spatial features and temporal dependencies in the carbon market data. Moreover, a residual error correction scheme is added to further improve prediction accuracy by modeling systematic forecasting errors from the first prediction stage.

The uniqueness of the given research work lies in combining heterogeneous data sources and advanced deep learning methods in a single predictive framework. In contrast to traditional carbon price prediction models that use only structured numerical data, the proposed framework integrates financial variables with sentiment data derived from textual data. Additionally, the model proposes an interval prediction strategy to reflect market uncertainty and a two-stage residual error correction mechanism to enhance forecast reliability. This combined strategy allows the proposed system to capture complex nonlinear correlations, temporal relationships, and contextual market data in concert. The key findings of the research are as follows:

- (i) A hybrid ML–NLP forecasting model is established to combine structured financial indicators and sentiment features of textual data and, thereby, describe carbon market dynamics more comprehensively in the first step.
- (ii) Second, CNN–BiLSTM–attention deep learning is suggested to represent a combination of spatial interaction between features and long-term temporal dependence of price data on carbon.
- (iii) Third, a range of possible carbon prices is predicted using an interval prediction approach, making the model identify market uncertainty better than standard point prediction strategies.
- (iv) Fourth, a two-step mechanism of residual error correction is integrated to minimize the systematic effect of prediction bias and enhance the overall forecasting accuracy.

The rest of this article is structured as follows. Section 2 analyzes related literature on carbon price prediction and ML-based forecasting techniques. Section 3 provides the suggested hybrid ML–NLP forecasting model. Section 4 explains the experimental design, the dataset, and the

implementation setup. Section 5 presents the results and experimental analysis. Lastly, Section 6 provides the conclusion and directions for future research.

2. Related works

Accurate forecasting of carbon prices is important for supporting the creation of the carbon trading market and the planning of environmental policies. Carbon prices are highly volatile and nonlinear due to the interplay of energy markets, economic indicators, and environmental regulations. Consequently, there has been an investigation into different forecasting methods, from conventional statistical models to newer deep learning methods.

Initial research was largely based on statistical and econometric prediction of carbon prices. Widely used models to measure carbon market volatility and price dynamics include autoregressive integrated moving average and generalized autoregressive conditional heteroskedasticity (Qin *et al.*, 2024). Such models can indeed model simple temporal dependencies, but the performance is usually poor with nonlinear patterns and high-dimensional financial information.

To address these drawbacks, ML algorithms have been proposed in carbon price forecasting. Support vector regression, decision trees, and random forest models have been used to approximate the nonlinear relationship between carbon prices and the factors that affect them (Xu *et al.*, 2022). These methods were found to be more predictive than classical statistical models, but still had difficulties in modeling long-term temporal relationships found in time-series data.

As deep learning methods have evolved, the use of neural network models in finance and energy market forecasting has become more popular. LSTMs are specifically successful in the sequential dependencies of time-series datasets (Dong *et al.*, 2023). Several studies have also shown that LSTM-based models are more effective at predicting carbon price changes than traditional ML models (Shi *et al.*, 2024). Moreover, other effective alternatives that have been employed as efficient in modeling sequential data in the carbon markets are gated recurrent unit networks (Zou & Zhang, 2024).

Further improvement in prediction has been offered with the help of hybrid deep learning architectures. CNNs can extract local and spatial properties in the input variables, whereas recurrent neural networks can capture temporal relations in sequential data (T. Zhang & Tang, 2023). A combination of CNN and LSTM has been demonstrated to achieve better results in financial forecasting problems, as a consequence of its capacity to

acquire both spatial and temporal feature representation (Y. Wang, Qin, *et al.*, 2023).

There have also been attention mechanisms which are meant to enhance the effectiveness of deep learning models in time-series prediction. Attention-based neural networks enable models to concentrate on the most valuable input features or time steps, enhancing prediction accuracy and intelligibility (K. Zhang *et al.*, 2023). BiLSTM models with attention layers have been effectively used in financial market forecasting to capture dependence between past and future contexts (K. Sun & Fan, 2026).

Besides improving the model architecture, researchers have attempted to use multi-source data in carbon prediction. These include energy prices, macroeconomic variables, and environmental policy variables as external variables affecting carbon markets (X. Zhang *et al.*, 2023). These multi-factor models provide a more detailed view of market dynamics and also improve forecasting performance.

The second research focus includes hybrid decomposition-based models. Various prediction models were developed to predict the carbon price, with empirical mode decomposition and variational mode decomposition being the techniques used on a complex series of the carbon price (Feng *et al.*, 2023). As models can learn low-, medium-, and high-frequency patterns, the techniques reduce noise and improve prediction efficacy.

Textual data has also recently been taken into account in financial prediction models using NLP techniques (Mujiono *et al.*, 2025). News, policies, and social media discussions can influence investor actions and market sentiment (Mao & Zeng, 2023). Sentiment analysis methods extract emotional cues from textual data that can enhance predictive forecasting models (Y. Wang, Wang, *et al.*, 2023).

Previous studies suggested that advanced artificial intelligence techniques for forecasting increasingly complex energy, environmental, and financial systems are required. Models based on hybrid deep learning architectures, optimization-based forecasting approaches, and multimodal learning frames have been robustly demonstrated to offer enhanced predictive performance in complex datasets through their ability to capture the nonlinear interactions between parameters operating at various timescales and the temporal dependencies in the underlying processes (Irshad *et al.*, 2024; Shaikh *et al.*, 2022; M.C. Wang *et al.*, 2024). Moreover, integrated energy management and data-driven decision-support systems are increasingly being studied to exploit multiple information sources and improve prediction reliability under uncertain

operating conditions (Conteh *et al.*, 2021; Huang *et al.*, 2021). Recent research also highlights intelligent optimization, uncertainty-aware forecasting, ML, and other algorithms to improve forecasting accuracy and support sustainable energy and environmental decision-making (Sedighi *et al.*, 2022). Recent research trends indicate a growing attention to integrating heterogeneous data sources and advanced learning mechanisms within unified forecasting frameworks. This provides strong motivation for the hybrid ML–NLP approach we propose.

Recently, developments in artificial intelligence and optimization have shown significant potential for addressing complex energy system challenges beyond carbon price forecasting. Gaber *et al.* (2025) proposed a cuckoo search algorithm-based approach for optimizing load frequency control in interconnected power systems, highlighting the growing importance of intelligent optimization in modern energy applications. These developments further motivate the adoption of advanced artificial intelligence-driven frameworks for complex prediction and decision-support tasks, including carbon price forecasting under dynamic market conditions.

In the financial forecasting and time-series field, transformer-based architectures have received considerable attention because of their ability to model long-range temporal dependencies. Recent studies have demonstrated their effectiveness in improving carbon price forecasting accuracy under highly nonlinear market conditions (Wu & Du, 2024). Models such as Transformer, Informer, Autoformer, and FEDformer have proven promising on complex time-series forecasting tasks. Along with this, pre-trained models like BERT, GPT, etc., have improved sentiment extraction as well as contextual understanding of financial news and policy-related text data. Combining these models with frameworks for forecasting carbon prices is a great option for future research.

In addition to improving forecasting accuracy, recent studies have highlighted the importance of explainable artificial intelligence in carbon price prediction. Explainable deep learning techniques enhance model transparency by providing insights into the contribution of input features, thereby improving the reliability and interpretability of forecasting models for practical decision-making (Sayed *et al.*, 2024).

While forecasting carbon prices has improved substantially, the literature has many limitations. Many studies examine structured numerical variables and miss the richness and information that can be extracted from unstructured text, such as policy announcements from banks, news items, and social media discussions on Twitter,

StockTwits, and Reddit. Furthermore, most forecasting methods provide only point forecasts and are not capable of adequately quantifying market uncertainty via interval forecasts. Additionally, the unification of sentiment-based information, deep learning architectures, and residual error correction within forecasting is also an area that has received little attention. These gaps provide the rationale for the hybrid ML–NLP framework proposed in this study, which combines structured and unstructured information with interval prediction and residual learning to enhance forecasting performance.

3. Proposed framework

This study proposes a hybrid intelligent forecasting system that combines NLP methods with a deep learning-enabled interval prediction system. The aim of the proposed system is to achieve accurate carbon price prediction by integrating both structured financial features and unstructured textual data into a single learning pipeline. The framework combines sentiment-enhanced feature extraction with a hybrid CNN, BiLSTM, and attention mechanism, with an adaptive error-correction stage. The general architecture takes heterogeneous market information and generates interval-value forecasts representing uncertainty in carbon price changes.

Sentiment analysis involves pre-processing text obtained from news articles, policy announcements, and social media discussions for tokenization, stop-word removal, and text normalization. Sentiment scores were generated using polarity-based sentiment analysis, yielding positive, negative, and neutral sentiments. The sentiment indicators were aggregated over each forecasting period and transformed into numerical sentiment feature vectors. The extracted sentiment features were then merged with structured financial indicators and given to the CNN–BiLSTM–attention prediction model.

The system initially gathers structured financial variables, including past carbon price, power market variables, and macroeconomic variables. In addition to numerical variables, unstructured textual data from news reports, policy announcements, and social media discussions were also used in the prediction process. NLP techniques were employed to process the textual data and extract sentiment signals, which were used to create market expectations and investor perceptions. Such sentiment signals were then combined with structured financial characteristics to create a combined representation, which was used by the forecasting model (H. Zhang *et al.*, 2025).

Figure 1 shows the full hybrid ML–NLP pipeline design of interval-valued carbon price forecasting. The

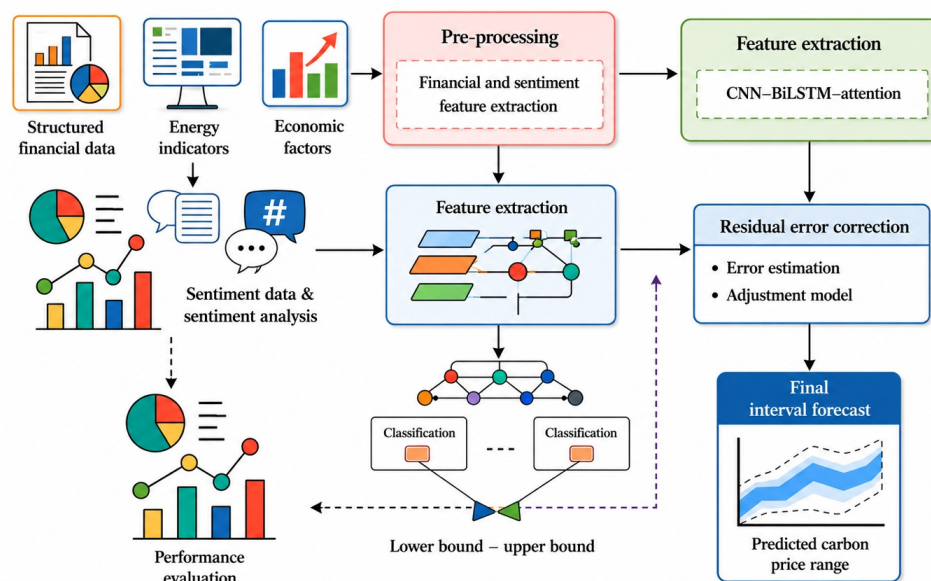


Figure 1. Hybrid machine learning–natural language processing framework for interval carbon price forecasting
Abbreviations: BiLSTM: Bidirectional long short-term memory; CNN: Convolutional neural network.

framework combines both structured financial indicators and unstructured textual data. The fused features then underwent a CNN–BiLSTM–attention prediction model after pre-processing and sentiment extraction of the data. A residual error correction module adjusted the forecast to produce final interval-based carbon price forecasts.

Let the structured market indicators at time step t be represented as a feature vector (**Equation 1**):

$$X_t = \{x_{1,t}, x_{2,t}, x_{3,t}, \dots, x_{n,t}\} \quad (1)$$

where n represents the number of numerical variables, including the history of the carbon price, the energy price, and the economic indicators. The sentiment data generated from textual material is shown in **Equation 2**:

$$S_t = \{s_{1,t}, s_{2,t}, s_{3,t}, \dots, s_{m,t}\} \quad (2)$$

where m is the number of sentiment-related features obtained by analyzing the text. The two forms of features were combined to constitute a single feature representation, which is defined as **Equation 3**:

$$F_t = [X_t S_t] \quad (3)$$

where F_t represents a combination of the input vector at the prediction point.

3.1. Attention prediction model convolutional neural network–bidirectional long short-term memory

The hybrid deep learning architecture takes the fused

feature sequence and comprises a CNN, a BiLSTM network, and an attention mechanism. This architecture aims to capture spatial feature interactions, temporal dependencies, and feature importance simultaneously.

The CNN layer extracts local features by applying convolution filters to the input feature sequence. The convolution operation may be mathematically represented as (**Equation 4**):

$$h_t = f(W * F_t + b) \quad (4)$$

where W represents the convolution kernel, b indicates the bias term, and $f(\cdot)$ is the nonlinear activation function. The CNN layer captures intricate interactions among the sentiment indicators and the financial variables that determine the carbon price pattern.

The resulting extracted feature maps were submitted to a BiLSTM network to identify the temporal relations in the carbon price time series. The LSTM network represents sequential relations using a memory state that can vary over time. The state of the LSTM at time t that is not observable can be represented as **Equation 5**:

$$h_t = \text{LSTM}(h_{t-1}, x_t) \quad (5)$$

where h_t represents the hidden state at time t . In the bidirectional arrangement, the sequence is also processed in forward and backward directions to capture all temporal dependencies. The hidden representation is the combination of hidden representations of both the mean and the variance, as defined by **Equation 6**:

$$h_t^{b_i} = [\overleftarrow{h}_t, \overrightarrow{h}_t] \quad (6)$$

where $\overleftarrow{h}_t$ and $\overrightarrow{h}_t$ represent the forward and backward hidden states, respectively. To give the model more prediction power, an attention mechanism was proposed to dynamically assign weights of importance to the hidden states. The time step attention score was calculated using **Equation 7**:

$$e_t = v^T \tanh(W_h h_t + b_h) \quad (7)$$

where W_h and b_h represent parameters to be learnt, and v represents the attention weight vector. SoftMax was used to obtain the normalized attention weight (**Equation 8**):

$$\alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^t \exp(e_i)} \quad (8)$$

The weighted temporal features were then determined and represented as a context vector (**Equation 9**):

$$c = \sum_{t=1}^T \alpha_t h_t \quad (9)$$

This mechanism enables the model to focus on the most informative time steps when forecasting carbon price movements.

3.2. Interval strategy of prediction

The proposed framework was used to predict an interval of the possible range of carbon prices instead of single-point forecasts. Interval prediction better captures uncertainty and volatility in carbon markets. The upper and lower prediction limits were determined as (**Equation 10**):

$$P_L = f_L(c); P_U = f_U(c) \quad (10)$$

where P_L and P_U are the minimum and maximum of the price range being predicted, and c represents the context vector generated by the attention mechanism.

3.3. Two-stage error correction process

Even after deep learning models have learned complex nonlinear relationships, prediction errors might still occur because of model bias or sudden market changes. To overcome this drawback, a second-level error correction unit was added to the forecasting system. This step models the residual error between the predicted price and the actual market price. The prediction error at time t is defined as **Equation 11**:

$$E_t = Y_t - \hat{Y}_t \quad (11)$$

where Y_t represents the observed price of carbon, and $\hat{Y}_t$ denotes the forecast, which is the result of the initial step

of the model. These prediction errors were then predicted in a sequence using a secondary learning aim which determines patterns in the residual errors (**Equation 12**):

$$\hat{E}_t = g(E_{t-1}, E_{t-2}, \dots, E_{t-k}) \quad (12)$$

where $g(\cdot)$ is the remaining learning functional and k represents the number of past error observations that are utilized in the prediction process. The carbon price forecast was corrected and obtained as the final forecast (**Equation 13**).

$$Y_t^{\text{final}} = \hat{Y}_t + \hat{E}_t \quad (13)$$

The role of this correction stage is to enhance the predictive accuracy of the first-stage prediction by correcting systematic bias in the prediction.

4. Experimental setup

The proposed forecasting framework was implemented and evaluated using a high-performance computing environment to efficiently train the CNN-BiLSTM-attention network and the residual error correction module. The experiments were conducted on a workstation equipped with an Intel Core i7 processor (3.4 GHz), 16 GB RAM, and an NVIDIA GeForce RTX 3060 GPU with 12 GB memory. The proposed model was developed using Python (version 3.10.12), with TensorFlow (version 2.15.0) and Keras frameworks (version 2.15.0) used for deep learning model development and training. Data processing, feature preparation, and performance evaluation were carried out using NumPy (version 1.26.4), Pandas (version 2.1.4), and Scikit-learn (version 1.3.2) libraries.

The experimental analysis was performed in a Linux-based environment using Ubuntu 22.04 to ensure stable execution of GPU-accelerated deep learning operations. Real-world carbon market datasets, including European Union Emission Trading System (EU ETS) carbon allowance prices and China Emission Trading System (China ETS) carbon price data, were used for model validation. The datasets contain historical carbon price information along with relevant market variables such as opening price, closing price, trading volume, energy-related indicators, and macroeconomic factors. In addition to structured market information, textual data collected from financial news articles, carbon policy announcements, and market-related discussions were incorporated to generate sentiment-based features.

Textual data were collected from financial news articles, official carbon policy announcements, and publicly available market-related discussions. The text data were pre-processed through lowercasing, tokenization, stop-

word removal, punctuation removal, and lemmatization. Sentiment analysis was performed using the VADER sentiment analyzer to obtain positive, negative, neutral, and compound sentiment scores. These sentiment scores were aggregated over each forecasting interval and combined with the structured market variables to construct the input feature vector for the proposed CNN–BiLSTM–attention model.

Before training the model, missing values were handled using an appropriate interpolation technique, and all input variables were normalized through min–max scaling within the range of [0,1]. The time-series research data were converted into sequential input samples using an elementary sliding-window approach, where analysis of past carbon market data was used to predict future intervals of carbon prices. The data were partitioned into a training set (70%), a validation set (10%), and a testing set (20%) in chronological order to preserve the order of carbon market data and prevent information leakage.

Hyperparameter tuning for performance validation was performed through experimentation for the CNN–BiLSTM–attention model. First, local interactions among carbon price indicators and sentiment-related features were assessed using the CNN layer to identify their effect. In the second step, the BiLSTM layer captured long-term temporal dependencies within the sequential market data. We incorporated an attention mechanism to weight time steps of greater importance to improve forecast reliability. The model was trained using the Adam optimization algorithm, which involved updating the network parameters with a gradient-based optimization method until convergence.

The secondary model was an error correction module for the forecasting model. The forecasting errors of the primary learning CNN–BiLSTM–attention model were modeled in the secondary CNN–BiLSTM–attention model and used to correct the output prediction. To ensure the reliability and stability of the proposed framework,

all experiments were independently repeated 30 times using different random initializations while maintaining the same training, validation, and testing datasets. The reported performance metrics correspond to the average results obtained across the 30 independent runs.

5. Results and discussion

This section describes the experimental results using the proposed hybrid CNN–BiLSTM–attention framework with residual error correction for forecasting carbon price intervals. To assess the predictive ability of the proposed model, real-world carbon-market datasets, EU ETS allowance prices and China ETS carbon price data were used. This analysis aims to examine the proposed model's ability to detect nonlinear price, temporal, and uncertainty patterns in carbon allowance markets by integrating structured market data and unstructured textual features based on sentiment.

The carbon market data we collected consists of historical carbon allowance prices and other financial and market variables. The dataset incorporates carbon price data, trading volume, energy market variables, and macroeconomic indicators collected from the chosen analysis period. Furthermore, data from financial news articles and carbon policy announcements were converted into information features and combined with numerical market variables for prediction.

To prepare the data for training, missing value imputation, normalization, and sequencing were performed. Using a sliding-window approach, input sequences were formed from time-series observations. The CNN–BiLSTM–attention model learnt from historical price patterns to predict future carbon price intervals. To preserve the temporal characteristics of the carbon market data, the dataset was split into training (70%), validation (10%), and testing (20%) sets. Table 1 presents the statistical summary of the major variables used in the carbon price forecasting experiments.

Table 1. Statistical summary of carbon market dataset variables

Variable	Mean	Minimum	Maximum
European Union Emission Trading System carbon allowance price (€/tCO ₂)	58.42	15.20	98.65
China Emission Trading System carbon allowance price (€/tCO ₂)	9.14	4.85	13.52
Trading volume (million tonnes)	12.74	0.85	46.30
Energy price index	104.56	82.40	148.75
Market sentiment score	0.18	−0.74	0.86

The statistical properties of variables used in the carbon price forecasting tests are shown in Table 1. The price of the EU ETS allowance shows substantial variation over the investigated period, influenced by conditions in the energy markets and changes in regulations and policies to reduce emissions. Similarly, the China ETS carbon price was converted into €/tCO₂ to allow for comparable analysis of its fluctuations, associated with market development and policy changes. The volume traded did not remain the same but varied frequently. The computed value, which captures opinions, takes on negative and positive values to denote changes in public and investor perceptions, extracted from texts. These changes affirm the nonlinearity and dynamics of the carbon market, therefore supporting the use of advanced deep learning models for interval-based forecasting.

According to Figure 2, the allowance price in the EU ETS market has been increasing steadily. The carbon price series experienced substantial changes, which can be attributed to energy market conditions, regulatory changes, emission reduction policies, and market sentiment. The EU ETS price began with a slight increase, then rose significantly due to market mechanisms and rising demand for emission allowances driven by policy interventions. In times of greater uncertainty and volatility in energy prices, the price increased to a higher level before fluctuating in the later period. Similarly, the price of the ETS in China progressively rose, with periodic fluctuations due to market development, trading activity, and regulatory changes.

The observed volatility and nonlinear movements indicate the complexity of carbon markets, driven by the interaction of many economic and environmental factors influencing price behavior. The presence of temporal series and non-constant variance reflects variation in carbon price data, making it suitable for an advanced deep learning approach. One such approach, the CNN-BiLSTM with an attention mechanism, can be used for accurate interval-based forecasting.

As illustrated in Figure 3, the actual carbon allowance prices are contrasted with the forecasting results generated by the proposed CNN-BiLSTM-attention model and the residual error-correcting mechanism. The carbon price curve obtained from the forecasting exercise closely tracks the actual path during the testing period. This integrated moving average model thus has the capacity to capture both short-run price fluctuations and the long-run temporal dependencies of the carbon price.

For instance, the actual carbon allowance price was about 82.5 €/tCO₂ when the proposed model projected around 81.7 €/tCO₂, a small forecasting error. During periods of increased volatility, the model tracked the actual

price variations around 88.6 €/tCO₂, with only a minor difference between the actual and predicted values. The two curves closely correspond, indicating that the error correction residual module reduces prediction bias and increases prediction accuracy.

The hybrid CNN-BiLSTM-attention framework can capture complex nonlinear relationships in carbon price time series data. The stronger relationship between actual and predicted values confirms that using neural networks for deep temporal feature extraction, weighting feature influence using an attention mechanism, and residual learning could provide reliable interval forecasts of carbon price.

Table 2 shows the CNN-BiLSTM-attention model prediction of the initial carbon price and the maximum prediction after residual error correction. The first forecasting stage recorded a mean absolute error (MAE) of 2.84 €/tCO₂, indicating that the deep learning architecture was able to comprehend the main elements affecting the carbon price. After adding the residual adjustment module, the post-enrichment error was 1.76 €/tCO₂. Based on lower-secondary residual learning, forecasting deviation can be a good indicator that can enhance the forecasting accuracy of the carbon price.

Table 2. Prediction comparison before and after residual error correction

Model output	Mean absolute error (€/tCO ₂)
Convolutional neural network–bidirectional long short-term memory–attention prediction	2.84
After residual error correction	1.76

The forecasting performance of the proposed framework was compared against multiple classical and deep learning-based models (Table 3). According to the autoregressive integrated moving average model, the forecasting error was higher because they were not able to capture nonlinear relationships in the carbon market. ML methods like support vector regression provided a higher level of performance. However, such techniques still face challenges in accommodating advanced temporal dependencies.

The deep learning models gated recurrent unit and LSTM performed well because they can learn patterns from past carbon price data. By combining local feature extraction and temporal learning capabilities, the CNN-LSTM model further improved the performance. Using



Figure 2. Time-series variation of carbon allowance prices in the European Union Emission Trading System (EU ETS) and China Emission Trading System markets

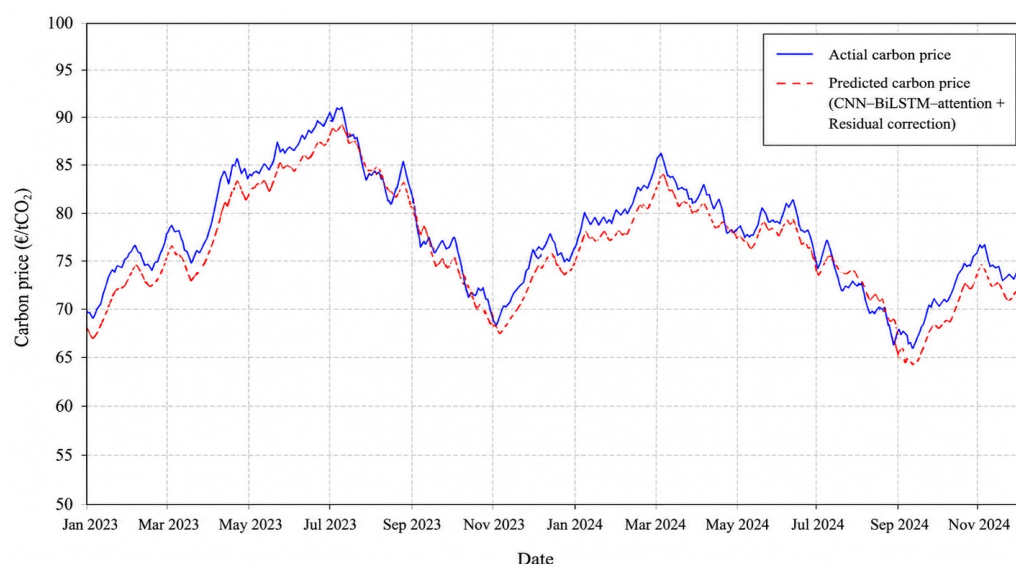


Figure 3. Actual and predicted carbon allowance prices during the testing period

Table 3. Performance comparison with baseline forecasting models

Model	MAE (€/tCO ₂)	RMSE (€/tCO ₂)	MAPE (%)	R ²
ARIMA	5.26	7.14	10.24	0.82
SVR	4.18	5.96	8.15	0.86
GRU	3.42	4.85	6.72	0.90
LSTM	3.05	4.36	5.94	0.92
CNN-LSTM	2.74	3.92	5.21	0.94
Proposed CNN-BiLSTM-attention	2.18	3.21	4.15	0.96
Proposed + residual correction	1.76	2.74	3.62	0.97

Abbreviations: ARIMA: Autoregressive integrated moving average; BiLSTM: Bidirectional long short-term memory; CNN: Convolutional neural network; GRU: Gated recurrent unit; LSTM: Long short-term memory; MAE: Mean absolute error; MAPE: Mean absolute percentage error; RMSE: Root mean square error; SVR: Support vector regression.

bi-directional temporal learning and attention-based feature selection, the proposed CNN-BiLSTM-attention model achieved an MAE of 2.18 €/tCO₂ and an R^2 of 0.96.

Once the residual error correction mechanism was introduced, the proposed framework achieved the lowest MAE of 1.76 €/tCO₂, a root mean square error (RMSE) of 2.74 €/tCO₂ and the highest R^2 value of 0.97. Based on forecasting model performance, the reliability measure demonstrates the effectiveness of the residual correction stage in reducing systematic forecasting errors. Furthermore, it improves the overall performance of the carbon price forecasting framework.

Figure 4 illustrates the distribution of the residual forecasting errors produced by the hybrid forecasting framework proposed in this study. Here, the residual error is defined as the carbon allowance price minus the value predicted by the CNN-BiLSTM-attention model after the residual correction stage. The histogram shows that most residuals are extremely small, indicating that the proposed model produces predictions with low systematic bias.

Most prediction errors were concentrated in a relatively small region around the central region, while only a limited number of far deviations were observed during times of high volatility. Larger deviations can be explained by shifts in carbon market behavior after regulatory announcements, as energy prices and external economic factors affect behavior. Residual values were close to zero, showing the effectiveness of the proposed mechanism in reducing forecasting errors and improving prediction stability.

After including the residual error correction module, the mean forecasting error improved from 2.84 €/tCO₂ to 1.76 €/tCO₂. The secondary residual stage can efficiently detect and adjust the bias caused by the first forecasting phase, as the result illustrates.

The experimental results show that the proposed CNN-based feature extraction, BiLSTM-based temporal learning, attention-based feature selection, and residual error correction were effective for forecasting carbon prices. The suggested hybrid ML-NLP framework successfully captured nonlinear relations and time-varying patterns in the carbon market, thus enhancing the reliability of interval-based predictions of carbon allowance prices.

Table 4 demonstrates the success of the residual error correction mechanism. The first model, CNN-BiLSTM-attention, demonstrated an MAE of 2.84 €/tCO₂ and an RMSE of 4.12 €/tCO₂. The residual correction step helped reduce the forecasting error to an MAE of 1.76 €/tCO₂ and an RMSE of 2.74 €/tCO₂. This shows a significant reduction in prediction error, which demonstrates that the secondary

residual learning module effectively compensates for systematic forecasting errors.

Table 5 shows the computational complexity of different forecasting techniques. Compared to other models, autoregressive integrated moving average and support vector regression required less computational time because of their simpler model structure. Deep learning techniques needed more training time because of the complex network architecture. The design of the suggested CNN-BiLSTM-attention model had a slightly higher computational cost, but it improved forecasting capability by capturing nonlinear relationships and long-term dependence in the carbon price time-series data.

Table 6 reports the proposed framework's ability to estimate uncertainty. A prediction interval coverage probability value of 0.94 was obtained, indicating that 94% of the actual carbon price observations were contained within the predicted interval. The prediction interval width value implies that the model provided a reliable forecast with a sensible interval width.

Tables 6, 7, and 8 show the interval prediction performance, model configuration, and contribution of each part of the model. The selected hyperparameters of the CNN-BiLSTM-attention model are summarized in Table 7. The model was trained with the Adam optimizer, a learning rate of 0.001, a batch size of 64 and 50 epochs. Table 7 indicates that the proposed framework can generate reliable carbon price intervals with good coverage performance.

As shown in Table 8, we performed ablation studies to justify all the components. The CNN-only model was unable to capture sufficient temporal dependencies for accurate forecasting. However, with LSTM and BiLSTM models, we can learn the temporal features. The attention mechanism was added to accurately predict temporally important features. In summary, a complete model that includes residual error correction yielded the lowest MAE of 1.76 €/tCO₂. This reveals that each component contributes to improving carbon price forecasting.

To further validate the superiority of the proposed framework, statistical significance analysis was conducted using a paired *t*-test (Python 3.10.12, SciPy 1.11.4) based on 30 independent experimental runs. The forecasting errors of the proposed CNN-BiLSTM-attention model with residual error correction were compared with those of the strongest baseline (CNN-LSTM). The analysis confirmed that the proposed model achieved a statistically significant improvement in forecasting performance ($p < 0.05$), indicating that the observed performance gains were consistent across repeated runs rather than resulting

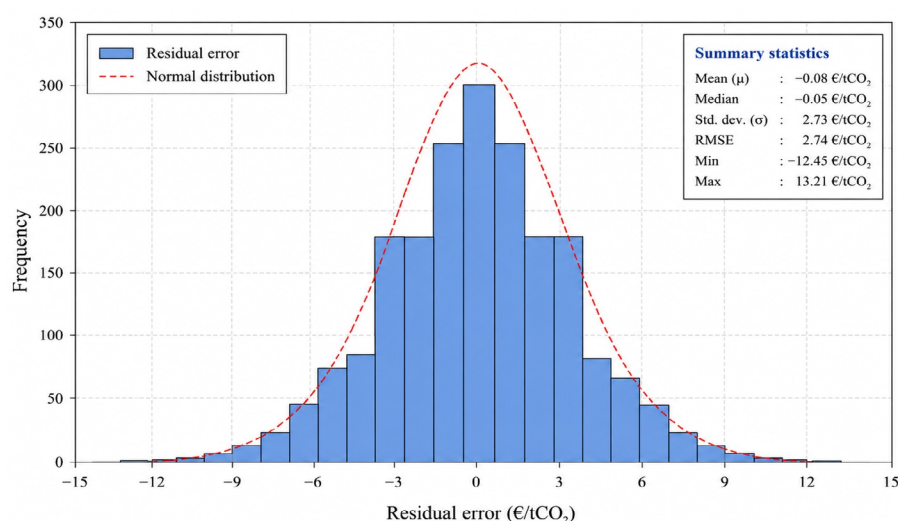


Figure 4. Residual error distribution

Table 4. Prediction improvement after residual error correction

Model stage	MAE (€/tCO ₂)	RMSE (€/tCO ₂)
CNN-BiLSTM-attention (initial prediction)	2.84	4.12
Residual error correction	1.76	2.74
Improvement (%)	38.1%	33.5%

Abbreviations: BiLSTM: Bidirectional long short-term memory; CNN: Convolutional neural network; MAE: Mean absolute error; RMSE: Root mean square error.

Table 5. Training complexity of forecasting models

Model	Parameters	Training time (s)	Prediction time (ms)
ARIMA	Low	45	5
SVR	Medium	82	8
LSTM	High	210	15
CNN-LSTM	High	240	18
Proposed CNN-BiLSTM-attention	High	265	20

Abbreviations: ARIMA: Autoregressive integrated moving average; BiLSTM: Bidirectional long short-term memory; CNN: Convolutional neural network; LSTM: Long short-term memory; SVR: Support vector regression.

Table 6. Interval prediction performance

Metric	Value
Prediction interval coverage probability	0.94
Prediction interval width	5.32 €/tCO ₂

Table 7. Hyperparameters of convolutional neural network–bidirectional long short-term memory–attention model

Parameter	Value
Convolutional neural network filters	64
Kernel size	3
Bidirectional long short-term memory units	128
Attention dimension	64
Batch size	64
Learning rate	0.001
Optimizer	Adam
Epochs	50

Table 8. Ablation study of model components

Model variant	MAE (€/tCO ₂)
CNN only	4.21
CNN + LSTM	3.45
CNN + BiLSTM	2.96
CNN + BiLSTM + attention	2.18
Full model + residual correction	1.76

Abbreviations: BiLSTM: Bidirectional long short-term memory; CNN: Convolutional neural network; MAE: Mean absolute error.

from random variation. Figure 5 presents the statistical comparison of forecasting errors obtained across 30 independent experimental runs using the paired *t*-test.

The results demonstrate that the proposed framework consistently achieved lower forecasting errors compared with the CNN–LSTM baseline.

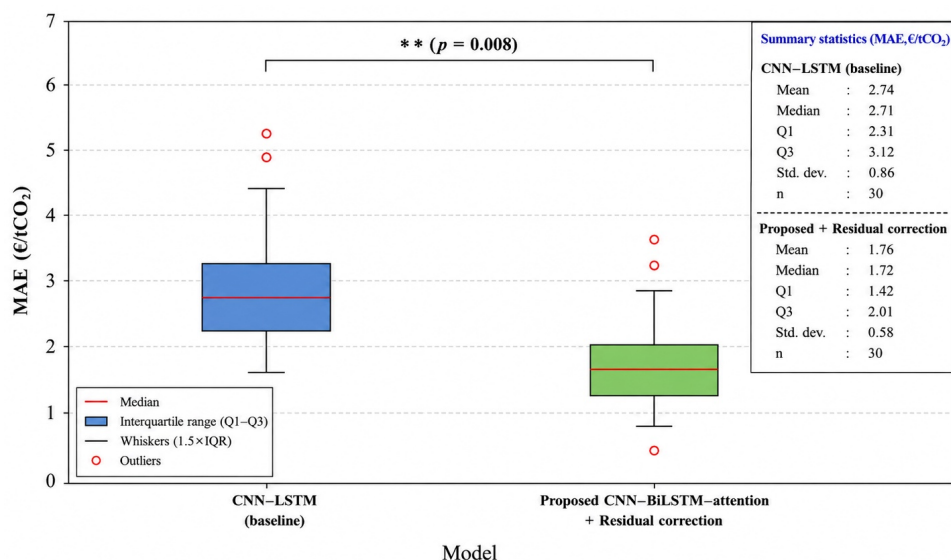


Figure 5. Statistical comparison of forecasting errors across 30 independent experimental runs using a paired *t*-test

Abbreviations: BiLSTM: Bidirectional long short-term memory; CNN: Convolutional neural network; MAE: Mean absolute error; RMSE: Root mean square error.

The proposed framework consistently outperformed conventional statistical and deep learning baseline models in terms of MAE, RMSE, mean absolute percentage error, and R^2 . The residual error correction module reduced the MAE by 38.1% and the RMSE by 33.5%, demonstrating its effectiveness in minimizing systematic forecasting errors. The statistical significance analysis further supports the robustness and reliability of the proposed forecasting framework. Future work should compare the proposed framework with recently developed transformer-based forecasting architectures to provide a broader performance evaluation.

6. Conclusion

This study proposed a hybrid ML–NLP forecasting framework with deep learning and sentiment-aware feature extraction for interval prediction and residual error correction to enhance carbon price forecasting performance. The framework employed a CNN–BiLSTM–attention architecture that incorporated structured market indicators and sentiment-based textual features to capture nonlinear patterns and temporal dependencies. A gap-forecast method and a residual error correction module were used to improve forecasting reliability.

The experimental results demonstrated that the proposed framework effectively captured complex carbon market dynamics and improved forecasting accuracy by reducing systematic prediction errors. Future research should focus on improving the computational efficiency and scalability of the framework for real-time forecasting applications. In addition, the model should be evaluated using emerging carbon markets to assess its generalizability under different market conditions. Future studies can also investigate explainable artificial intelligence techniques to improve model interpretability and incorporate additional external factors, including energy prices, macroeconomic indicators, and geopolitical events. Furthermore, transformer-based language models and multimodal data sources can be explored to further enhance forecasting performance.

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Conflict of interest

The authors declare they have no competing interests.

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Availability of data

Data will be made available upon request to the corresponding author.

Further disclosure

Authors are fully responsible for the originality, validity, and integrity of the content of their manuscript, including any material generated by GenAI tools.

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