

# Forecasting Carbon Trading in the Green Energy Economy Using Autoformer

Yangyuanli Xu, Xinhang Ge, Huixi He

International Bussiness School, Xi'an Jiaotong-Liverpool University, Suzhou, 215004, China

**Abstract.** Amid the global energy transition and expanding carbon markets, accurately forecasting carbon emission allowance (CEA) prices is crucial for effective policymaking and risk management. Existing models struggle to capture the non-stationary dynamics of carbon prices, which are driven by external shocks and inherent multi-scale periodicities. To address this, we propose a multivariate forecasting framework based on Autoformer. By leveraging the superior nonlinear forecasting capabilities of Autoformer and constructing multi-dimensional input feature vectors, the proposed method effectively captures latent periodic patterns embedded in time series data of CEA. Rigorous empirical evaluations demonstrate that our method significantly outperforms baselines.

**Keywords:** Carbon Price Forecasting; Green Energy; Time-Series Forecasting; Autoformer.

## 1. Introduction

In the context of a continuously expanding global carbon asset market, the precision and stability of carbon price forecasting have become a cornerstone supporting carbon-neutrality strategies and green energy investment decisions [1]. Accurate carbon price forecasting not only assists governments in formulating effective macroeconomic control policies and maintaining market stability but also guides enterprises in optimizing carbon asset management and mitigating financial risks, thereby fostering high-quality, green, and low-carbon development. Carbon price forecasting is widely recognized as a formidable task, as the price series exhibits highly non-linear and non-stationary characteristics. Previous research indicates that the non-stationary nature of the carbon market stems primarily from two sources:

(1) Price Mutations Driven by External Factors: carbon market is highly susceptible to shocks from external factors, including macroeconomic policies, energy prices, and significant societal events [2].

(2) Superposition of Inherent Multiple Periodicities: The carbon market itself is subject to complex periodic patterns [3]. For example, the concentration of annual compliance obligations by enterprises leads to seasonal price fluctuations. To achieve more accurate medium- to long-term forecasting of carbon trading prices, scholars have proposed a variety of methods. While these methods have, to some extent, improved model fitting capabilities, they still face several challenges. For example, linear models assume fixed relationships between variables, making them ill-suited to capture abrupt changes triggered by policy shifts [4].

This study aims to address the two core issues contributing to the instability of the carbon market. To tackle the mutations driven by external factors, we design a multi-dimensional feature engineering and multivariate input structure tailored to the unique characteristics of the carbon market. For the market's intrinsic complex periodicities, we introduce an innovative variant of the Transformer architecture—the Autoformer model [5].

The primary contributions of this paper include:

- We leverage Autoformer to capture periodic features for the joint modeling and forecasting of multivariate time series, thereby effectively addressing the complex cyclical evolution patterns of the carbon market.
- We design a multi-dimensional feature engineering and multivariate input architecture tailored to the carbon market, effectively integrates exogenous variables [6].
- We conduct extensive experiments to demonstrate the effectiveness of our proposed method.

## 2. Related Work

In section, we summary the work of CEA price forecasting in three folds.

### 2.1 Classical Statistical Models

Early works of CEA price forecasting focus on classical statistical models, notably the Autoregressive Integrated Moving Average (ARIMA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models [7][8]. However, the inherent linear assumptions of these models and their dependence on manual feature engineering limit their ability to accurately capture the non-linear dynamics and policy-driven abrupt changes prevalent in the carbon market.

### 2.2 Recurrent Neural Networks

To overcome the linear constraints of traditional statistical models, deep learning methods, represented by Recurrent Neural Networks (RNNs), were introduced into the field of time-series forecasting [9][10]. Through their internal recurrent structure, RNNs enable the current hidden state to carry historical information, thereby effectively modeling temporal dependencies [11]. Despite the significant progress made by the RNN family in non-linear modeling, the issue of memory decay when handling exceptionally long sequences persists [12].

### 2.3 Transformer Model

To address the aforementioned issues, the Transformer architecture was adapted for time-series forecasting. Its core mechanism discards the recurrent structure, enabling parallelized training and enhancing the capture of long-range dependencies by directly calculating the relationships between any two points within a sequence [13][14]. However, the  $O(L^2)$  computational complexity of the standard self-attention mechanism makes it inefficient for processing long sequences (LTSF), and it inherently lacks the capability to explicitly model the multiple periodicities present in time-series data [15].

## 3. Method

In this section, we give the problem formulation of the CEA price forecasting, and present our method.

### 3.1 Problem Formulation

The forecasting of CEA prices can be framed as a Long-Term Time Series Forecasting (LTSF) problem [16]. The goal is to capture the complex dynamics of price and energy indicators as they evolve over time under multivariate input conditions, expressed as:

$$X = \{x_1, x_2, \dots, x_T\} \in \mathbb{R}^{T \times d}, \quad (1)$$

where  $T$  is the total length of the historical time series;  $d$  the feature dimension at each time step, encompassing variables such as carbon allowance price, wind/solar power output, electricity price, and temperature;  $x_T \in \mathbb{R}^d$  represents the multivariate observation vector at time step  $t$ .

The target sequence for prediction is denoted as:

$$Y = \{y_{T+1}, \dots, y_{T+O}\} \in \mathbb{R}^{O \times d'}, \quad (2)$$

W here  $O$  is the prediction horizon, representing the number of future time steps to be forecasted;  $d' \leq d$  is the dimension of the target variables to be predicted, which typically includes the carbon price and other core covariates.

The forecasting task is formally modeled as:

$$\hat{Y} = f_{\theta}(X_{T-I+1:T}), \quad (3)$$

where  $f_{\theta}$  is a deep forecasting model parameterized by  $\theta$ ;  $\hat{Y}$  is the model's forecast for the subsequent  $O$  time steps;  $X_{T-I+1:T}$  is the historical input window of length  $I$ .

### 3.2 Autoformer Model Structure and Modeling Mechanism

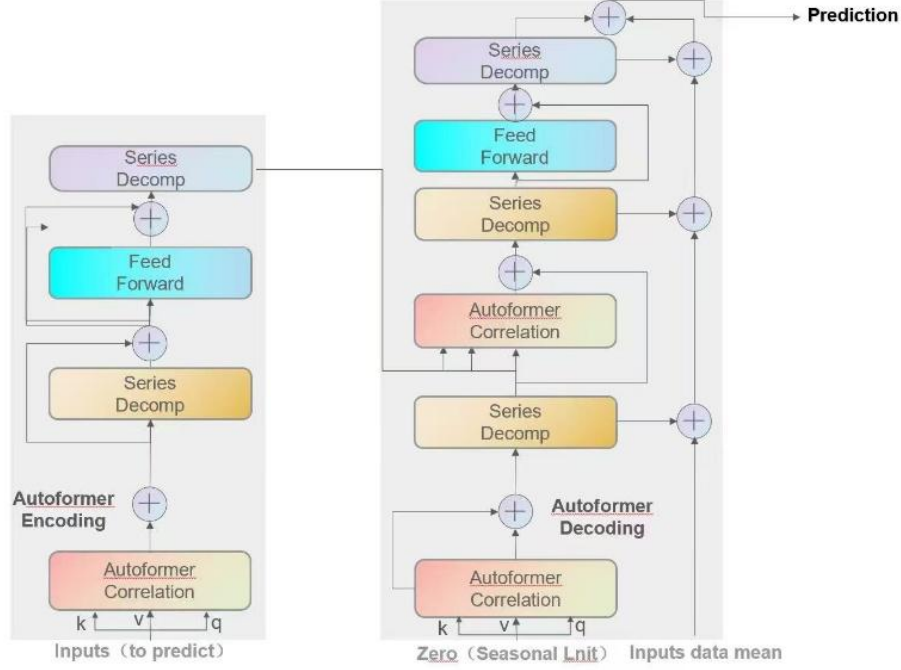


**Figure 1.** The Architecture of the Autoformer Model

The operational framework of the Autoformer is a modular, synergistic system comprising four principal components. Initially, the input preprocessing module executes data cleansing, normalization, and windowing to ensure high-quality, stable training samples [17][18]. Subsequently, the feature engineering module enriches the data by constructing a multi-dimensional feature set—incorporating temporal attributes, cross-variable interactions, and external variables—to enhance the model's perceptual and generalization capabilities [19][20][21][22][23]. The core of the framework is the Autoformer forecasting module, which employs a trend-seasonal decomposition mechanism to address non-stationarity and an Autocorrelation Mechanism to effectively capture long-range dependencies [24][25]. Finally, the output reconstruction module performs inverse normalization to revert predictions to their original scale and facilitates business-specific interpretation and evaluation [26]. This structured, decoupled architecture ensures both high prediction accuracy and excellent scalability for complex forecasting tasks in domains such as green energy and carbon trading. The overall workflow and interactions among these modules are illustrated in Figure 1, which provides a schematic view of the Autoformer's encoding-decoding process.

#### 3.2.1 Input Preprocessing and Feature Engineering

Before the data is input into the model, it undergoes systematic preprocessing [27]. To mitigate the impact of inconsistent scales among different variables on model performance, all continuous variables are normalized using the Min-Max method to map their values to the interval [28][29].

In the feature engineering phase, we select the following three categories of information as input features for the model, centered around the prediction target of "carbon market composite price", including:

- **Temporal Attribute Features:** This includes information corresponding to the date index, such as day, month, quarter, as well as temporal factors that may affect market trading activity, such as whether it is a public holiday.
- **Lagged Price Features:** Carbon price values from several past day are introduced as model inputs to capture the short-term trends and auto-correlative structure of the carbon market.
- **Auxiliary Variable Feature:** Variables such as temperature, energy prices, and renewable energy generation, which help provide additional contextual informatio.

For the sequence input constructed after feature engineering, a sliding window mechanism is employed to build modeling samples. Specifically, a window length  $L$  is set, and the window slides by a step (typically 1) at a time. The features of  $L$  consecutive time steps are used as the input sequence to predict the target variable values for the subsequent  $H$  time steps.

### 3.2.2 Intermediate Model Architecture

**Series Decomposition Mechanism.** Given an arbitrary input time series  $x_t = \{x_1, x_2, \dots, x_T\}$ , for  $t = 1, 2, \dots, T$  where the observation vector at each time step is  $x_t \in \mathbb{R}^d$ , Autoformer internally decomposes the input at each time step as follows:

$$x_t = s_t + t_t, \quad (4)$$

where  $x_t$  is the observation at the  $t$ -th time step of the original input sequence;  $s_t \in \mathbb{R}^d$  represents the seasonal component at this time step, designed to capture periodic fluctuations;  $t_t \in \mathbb{R}^d$  represents the trend component at this time step, designed to capture long-term, slowly varying trends.

To extract the trend component from the input, Autoformer utilizes a 1D Average Pooling operation as a smoothing filter:

$$t_t = \frac{1}{2k+1} \sum_{i=-k}^k x_{t+i}, s_t = x_t - t_t, \quad (5)$$

where  $k$  represents the sliding window size,  $t$  denotes the long-term trend estimated via a moving average, and  $s_t$  is the residual component obtained by subtracting the trend from the original signal, which primarily preserves the periodic and short-term fluctuation characteristics. During the model training process, this decomposition operation is dynamically performed at each layer to adapt to the extraction of structural features at different hierarchical levels.

**Autoformer Correlation.** The Autoformer architecture introduces a novel Auto-Correlation mechanism, supplanting the canonical point-wise self-attention of the Transformer. This series-level aggregation mechanism is designed to explicitly model periodic dependencies inherent in time-series data. Its fundamental objective is to identify the most significant periodic structures by calculating auto-correlation scores across all possible time lags ( $\tau$ ). This process quantifies the similarity between the current time series and its historical, time-delayed versions, thereby revealing dominant periodic patterns. The detailed architecture of this mechanism is illustrated in Figure 2, which leverages Fast Fourier Transform (FFT) to efficiently calculate correlations in the frequency domain and aggregate the results based on the most significant time delays.

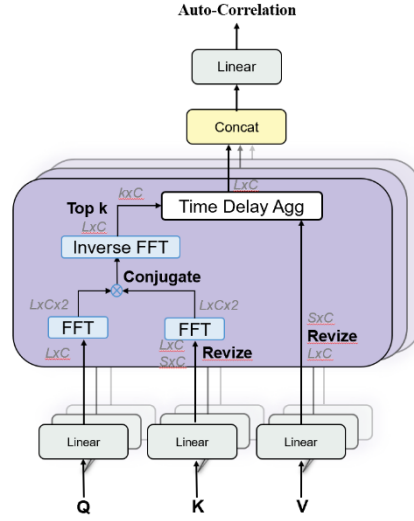


**Figure 2.** The Architecture of the Auto-Correlation Mechanism

### 3.2.3 Optimization Objective and Training Mechanism

To achieve long-term, accurate forecasting of carbon trading prices and green energy variables, we model this task as a typical supervised regression problem. Given an input window  $X_{in} \in \mathbb{R}^{I \times d}$  and its corresponding target output  $Y \in \mathbb{R}^{O \times d'}$ , we train a parameterized prediction function:

$$\hat{Y} = f_{\theta}(X_{in}), \quad (6)$$

where  $\theta$  is the set of trainable parameters of the Autoformer model;  $\hat{Y} \in \mathbb{R}^{O \times d'}$  is the model's prediction for the target variables over the next  $O$  time steps;  $d'$  is the dimension of the target variables to be predicted (typically a subset of key indicators like carbon price and energy prices).

We adopt the Mean Squared Error (MSE) as the loss function to measure the deviation between the model's predictions and the ground truth values [30]. Its mathematical expression is:

$$L_{MSE}(\theta) = \frac{1}{O \cdot d'} \sum_{t=T+1}^{T+O} \sum_{j=1}^{d'} \left( y_t^{(j)} - \hat{y}_t^{(j)} \right)^2, \quad (7)$$

where  $y_t^{(j)}$  is the ground truth value of the  $j$ -th target variable at the  $t$ -th future time step;  $\hat{y}_t^{(j)}$  is the corresponding model prediction.

The entire training process employs the Backpropagation algorithm and a Mini-batch Stochastic Gradient Descent (SGD) strategy, combined with the Adam optimizer, to iteratively update the parameters  $\theta$ : [31]

$$\theta \leftarrow \theta - \eta \cdot \nabla_{\theta} L_{MSE}(\theta), \quad (8)$$

where  $\eta$  is the learning rate;  $\nabla_{\theta} L$  is the gradient of the loss function with respect to the model parameters.

## 4. Experimental Evaluation

In this section, we introduce the dataset used for our experiments, detail the environmental and model configurations, and present a comprehensive analysis of the main results.

## 4.1 Dataset Description

This study utilizes a real-world dataset from China's national carbon market [32][33][34] to validate the proposed model's effectiveness. The primary data source is the Shanghai Environment and Energy Exchange, covering the period from its inception in July 2021 to the present. This dataset incorporates several crucial exogenous variables: the natural gas import price index (lng\_import\_index\_cn), the crude oil import price index (crude\_import\_index\_cn), the CNY/USD exchange rate (cny\_usd\_mid), and the carbon emission allowance (CEA) trading volume (cea\_volume\_cn).

For data preprocessing, we employed forward filling to handle any missing values. Outliers were identified and capped using the  $3\sigma$  principle, where values outside the range of  $[\mu - 3\sigma, \mu + 3\sigma]$  were replaced with the nearest boundary value. Finally, all features were normalized using Z-score standardization to eliminate scale differences. The complete dataset was chronologically partitioned into training, validation, and testing sets with a 7:2:1 ratio.

## 4.2 Experimental Setup

**Forecasting Task:** We adopt a rolling window mechanism, a standard practice in time-series forecasting.

**Baseline Models:** To rigorously evaluate the performance of Autoformer, we compare it against two methods that are widely used in time-series forecasting:

- **Transformer:** This model utilizes a self-attention mechanism to directly model relationships between all points in a sequence, effectively capturing long-range dependencies and overcoming the limitations of recurrent architectures.
- **Informer:** This model introduces an efficient ProbSparse self-attention mechanism, which solves the computational complexity problem of the standard Transformer when processing exceptionally long sequences.

**Implementation Details:** The model uses an input window (seq\_len) of 96 historical time steps (approximately three months) to predict a future horizon (pred\_len) of 24 time steps (approximately one month). Key model hyperparameters were standardized across experiments for fair comparison, including a hidden dimension (d\_model) of 512, 8 attention heads (n\_heads), 2 encoder layers (e\_layers), and 1 decoder layer (d\_layers). Models were trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. The Mean Squared Error (MSE) was used as the loss function. We also implemented an early stopping mechanism with a patience of 3 epochs to prevent overfitting. All experiments were conducted on an NVIDIA RTX 3090 GPU.

## 4.3 Experimental Results

This section presents a comprehensive evaluation of the model's performance, including quantitative metrics, a qualitative case study, and an analysis of feature importance.

### 4.3.1 Overall Performance Comparison

The quantitative results, measured by Mean Squared Error (MSE) and Mean Absolute Error (MAE), are summarized in Table 1.

**Table 1.** Prediction Errors of Various Models on the Carbon Price Dataset (pred\_len = 24)

| Rank | Model                               | CEA Dataset   |               |
|------|-------------------------------------|---------------|---------------|
|      |                                     | MSE           | MAE           |
| 1    | <b>Autoformer (Proposed Method)</b> | <b>0.4687</b> | <b>0.5880</b> |
| 2    | Transformer                         | 1.8864        | 0.9248        |
| 3    | Informer                            | 2.4439        | 1.1753        |

The results clearly demonstrate the superiority of the Autoformer model. It achieves the lowest error on both metrics, establishing itself as the most accurate model for this carbon price forecasting

task. Specifically, Autoformer improves upon the standard Transformer by 75.2% in MSE and 36.4% in MAE. The performance gap is even more pronounced when compared to Informer, with improvements of 80.8% in MSE and 50.0% in MAE. This significant outperformance can be attributed to Autoformer's innovative architecture. Its trend-seasonal decomposition mechanism effectively disentangles the complex periodic patterns from the underlying long-term trends inherent in carbon prices, while its series-level auto-correlation mechanism is more adept at capturing temporal dependencies than the point-wise attention used by its predecessors.

#### 4.3.2 Qualitative Analysis: Case Study Visualization

To provide a more intuitive understanding of the models' predictive behavior, Figure 3 visualizes their forecasts against the ground truth for a segment of the test set.

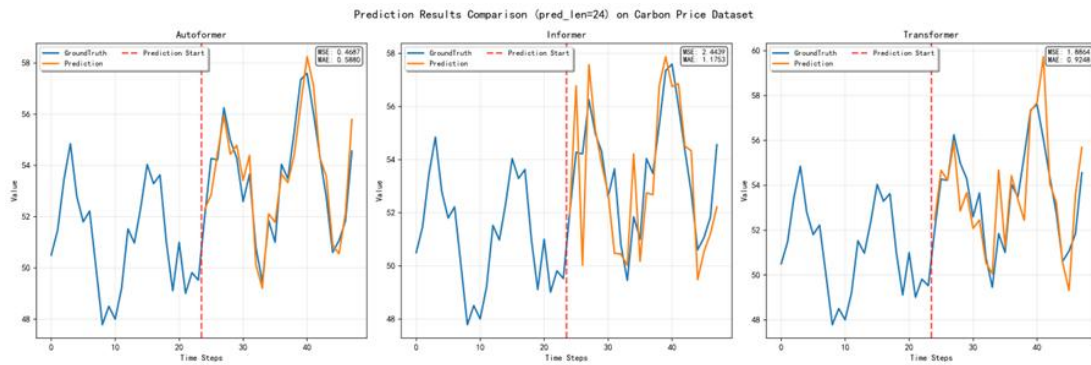


**Figure 3.** Prediction Results Comparison on Carbon Price Dataset (pred\_len = 24)

The visual analysis reveals distinct differences in the models' capabilities. While Transformer and Informer struggle to capture the market's dynamics, Autoformer aligns closely with the actual price movements. A detailed breakdown of the prediction window is as follows:

**Prediction Initial Phase (Time Steps 24-30):** All models show some initial lag. However, Autoformer's curve remains closest to the ground truth, whereas the other models deviate more significantly.

**Prediction Mid-Phase (Time Steps 30-40):** Autoformer successfully captures the periodic wave-like fluctuations in this period, whereas Informer's predictions are excessively volatile and Transformer's are overly smoothed.

**Prediction Late Phase (Time Steps 40-48):** This period contains a sharp "V"-shaped price reversal, which is a critical test of a model's foresight.

Autoformer excels here, accurately predicting both the downward turn and the subsequent sharp rebound. In contrast, both Transformer and Informer fail to anticipate this turning point, continuing their downward trajectory and thus accumulating significant error. This highlights Autoformer's superior ability to capture market momentum shifts.

#### 4.3.3 Analysis of Feature Importance

To validate the necessity of a multivariate approach and understand the contribution of each input variable, we conducted an experiment where the Autoformer model was trained using only a single feature at a time. The performance of these single-feature models was compared against the full multivariate model.

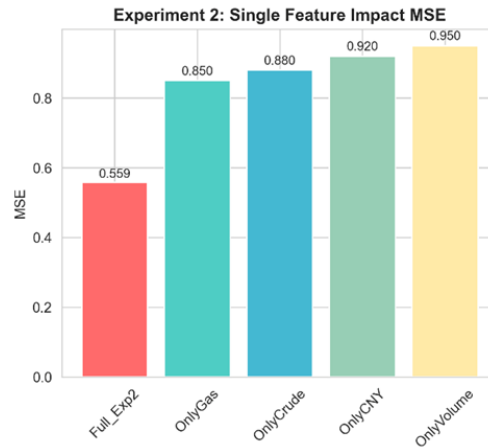


**Figure 4.** Single Feature Impact Analysis (MSE)

The results, shown in Figure 4, lead to two critical conclusions. First, the multivariate approach is essential. The full-feature model achieved an MSE of 0.559, which is substantially lower than the best single-feature model (Natural Gas, MSE=0.850). This confirms that carbon price is driven by a complex interplay of factors, and integrating multiple data sources is crucial for achieving high-precision forecasts, as any single variable provides an incomplete picture of the market dynamics. Second, the experiment reveals a clear hierarchy of influence exists among the features, ordered as Natural Gas Price > Crude Oil Price > CNY Exchange Rate > CEA Trading Volume. This ordering suggests an influence hierarchy of Energy Fundamentals > Macroeconomic Environment > Market Internal Behavior. The energy-related predictors are most potent because they have a direct causal link to carbon prices; for instance, natural gas prices directly influence fuel-switching decisions between gas and coal in the power sector, making it a strong leading indicator for carbon emissions and allowance demand. In contrast, the macroeconomic environment, represented by the exchange rate, has a more indirect and attenuated impact, as the information signal weakens through a longer causal chain.

Finally, market internal behavior, reflected by trading volume, is the weakest predictor because it is more of a lagging or coincidental indicator that captures reactions to known information and market noise rather than predicting future trends.

## 5. Conclusion

This study addresses the complex challenges of carbon price forecasting by developing and validating a novel framework that integrates targeted feature engineering with an advanced deep learning model. To capture the multifaceted drivers of the carbon market, we first designed a multi-dimensional feature set encompassing energy fundamentals (e.g., natural gas and crude oil prices), macroeconomic indicators, and internal market activity. We then introduced the Autoformer model to specifically analyze these time-series data, leveraging its unique series decomposition and auto-correlation mechanisms to effectively model the inherent non-stationary and multi-periodic patterns in carbon prices. The experimental results confirm the efficacy of our approach. The proposed Autoformer framework achieves superior prediction accuracy, significantly outperforming strong baselines like Transformer and Informer on both MAE and MSE metrics. Furthermore, our analysis underscores the critical importance of a multivariate design, as the full-feature model far surpassed the performance of any single-feature model, revealing a clear influence hierarchy where energy fundamentals act as the primary price driver.

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