Forecasting Carbon Price in China Using an ARIMA Integrated with ACNN-LSTM and XGBoost

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***Abstract*—China's carbon price (i.e. carbon emission trading price) is an important part of China's carbon market (i.e. carbon emissions trading market). The study of carbon price can be divided into two categories: the analysis of the influencing factors of carbon price, and the application of the carbon price forecasting models. Studies on influencing factors and carbon price forecasting models are often conducted independently, that is, the application of influencing factors in carbon price forecasting is often neglected. This paper incorporates the key influencing factors into the forecasting model to improve the credibility of the prediction results. Recently, a kind of hybrid forecasting model performs well in many fields and has not yet been used for carbon price prediction. This hybrid model combines ARIMA (Auto-Regressive Integrated Moving Average) with ACNN (Attention-based CNN), LSTM (Long Short-Term Memory), and XGBoost (eXtreme Gradient Boosting), making itself both interpretable and capable of processing extremely complex data. We denote this model as AALX (i.e. ARIMA integrated with ACNN-LSTM and XGBoost) and apply it to the field of carbon price prediction, after taking the key influencing factors of carbon price as the variable of the AALX model. Empirical results indicate that AALX not only retains the existing advantages, but also attains higher credibility.**

***Keywords*—carbon emission allowance, carbon emissions trading market, Pearson correlation coefficient, ARIMA, attention mechanism, LSTM, XGBoost**

I. Introduction

In the face of rising global temperatures, emission reduction has become the focus of China's policies [1]. In November 2021, the unified national carbon emissions trading market (i.e. carbon market) of China was officially launched [2]. China's carbon price (i.e. carbon emission trading price) is an important part of China's carbon market, the study of carbon price can be divided into the analysis of the influencing factors of carbon price and the application of carbon price forecasting models [3, 4].

In terms of the analysis of the influencing factors, the work of Zhou *et al.* [5], Lin *et al.* [6], Song *et al.* [7], Zhang *et al.* [8], indicated that both economic factors, environmental factors, and historical carbon price significantly affect current carbon price of China. The application of influencing factors in carbon price forecasting is often neglected. Until now, many carbon price forecasting researches are solely based on the historical data of carbon price [9], without considering the influencing factors. To deal with this problem, this paper analyzes the correlation between various factors and carbon prices, and then identifies nine key factors with high correlation with carbon prices, and uses these key factors as the variables put in the carbon price forecasting model.

In terms of carbon price forecasting models, existing models can be divided into three categories: Time Series Analysis (TS) models, Machine Learning (ML) models, and ML-TS hybrid models. ML models outperform TS models in processing complex-structured data but lack model interpretability. Traditional TS models are more interpretable, but not good at processing complex structured data. As for ML-TS hybrid models, currently, Liu *et al.* [10] proposed a GARCH-LSTM model with interpretability and the ability to process complex carbon price data. However, compared with a hybrid model in other fields [11, 12], the machine learning components in the GARCH-LSTM model [10] are relatively simple. That makes the GARCH-LSTM model potentially less effective when dealing with extremely complex data. On the contrary, the hybrid model proposed by Shi *et al.* [11, 12] combines ARIMA (Auto-Regressive Integrated Moving Average) with ACNN-LSTM (Attention-based-CNN-LSTM) and XGBoost (eXtreme Gradient Boosting), making itself both interpretable and capable of processing extremely complex data. This AALX (ARIMA integrated with ACNN-LSTM and XGBoost) model has not been used to forecast the carbon price. We are the first to apply the AALX model to carbon prices forecasting.

Our main contributions are as follows:

(1) We introduce a forecasting model called AALX, which has already performed well in other areas, into the field of carbon price prediction. The model demonstrates both interpretability and high accuracy.

(2) Since both the influencing factors and historical data can significantly affect the current carbon price, we innovatively use the key influencing factors of carbon price as the variables put in the AALX model, enhancing the credibility of the AALX model.

II. Literature Review

A. Literature about Influencing Factors of Carbon Price in China

To write this section, you will need to do a thorough literature search on different studies that relate to the broad topic of your research. This will introduce the readers to the area of your research. It would be ideal to organize them thematically and discuss them chronologically so that readers are aware of the evolution and progress in the field. In other words, separate themes should be discussed chronologically to highlight how research in those fields has progressed over time. This will highlight what has been done and what are the future directions that need to be worked upon.

There are many indicators of carbon price, which include the closing price of Carbon Emission Allowance (CEA) [13] and the China carbon trading price index [7], price of

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Emission Trading Scheme (ETS). Zhou *et al.* [5] explored the dynamic relationship between energy price, macroeconomic indicators, air quality, and China carbon price using data from the Hubei Emission Exchange. Lin et al [6] provided an analysis of the Emission Trading Scheme (ETS) in China, focusing on the factors that influence the ETS price. Song *et al.* [7] introduced a China carbon trading price index and analyzed the interrelationship between multiple factors and this index. Furthermore, the presence of long-term memory in carbon price in China was inferred through the serial auto-correlation test by Zhang *et al.* [8]. The aforementioned articles indicate that multiple influencing factors and historical data significantly impact current carbon prices.

B. Literature about Carbon Price Forecasting Models

Existing carbon price forecasting models can be divided into three categories: Time Series Analysis (TS) models, Machine Learning (ML) models, and ML-TS hybrid models.

In terms of traditional TS models, Zhang *et al.* [14] used the Generalized Auto-regressive Conditional Heteroskedasticity (GARCH) model to predict carbon price volatility in Shenzhen. Liu *et al.* [15] proposed a model that combined the GARCH model with Fractional Brownian Motion (FBM) to forecast carbon option price. From the research mentioned above, we can find that the traditional TS models emphasize the interpretability of the model but focus solely on the historical carbon price, ignoring the impact of multiple factors on carbon prices. Furthermore, traditional TS models perform poorly when processing complex-structured data.

In terms of ML models, Wang *et al.* [16] employed a DualStage Attention-Based Recurrent Neural Network (Seq2Seq model) to predict the price of the Hubei CEA. Zhang *et al.* [17] incorporate multiple influencing factors into the ML framework named ET-MVMD-LSTM to predict the carbon price. From the research mentioned above, we can conclude that ML models are able to deal with complex data but often suffer from a black-box feature and lack model interpretability.

To bridge the gap between TS models and ML models, Ji *et al.* [18] introduced a ML-TS hybrid model called ARIMA-CNN-LSTM model to predict carbon prices. Recently, Liu *et al.* [10] developed a ML-TS hybrid model called GARCHLSTM to predict carbon trading price. The ML-TS hybrid models mentioned above are both interpretable and capable of handling complex data. However, the ML components of the aforementioned ML-TS hybrid models are relatively simple, which makes themselves difficult to process extremely complex data. Xu *et al.* [11] introduced a ML-ARIMA hybrid model based on the attention mechanism of CNN-LSTM and XGBoost to predict air quality, Shi *et al.* [12] introduced an integration of an attention-based CNN-LSTM, XGBoost and ARIMA for stock prediction. Inspired by Xu *et al.* [11] and the work of Shi *et al.* [12], we introduce an AALX (ARIMA integrated with ACNN-LSTM and XGBoost) model to carbon price forecasting.

III. Influencing Factors Analysis and Data Acquisition

A. Influencing Factors Analysis

The relevant research indicated that the factors influencing China's carbon price can be primarily categorized into six major classes, namely, economic conditions, financial markets, international carbon markets, fossil fuel price, climate and environment, and other factors. The theoretical analysis of the impact of each factor on carbon price is as follows:

1) The impact of economic conditions on carbon price

Economic fluctuations can affect the supply-demand relationship and ultimately have an impact on a company's investment decisions and production strategies. All will have a significant impact on the demand for carbon emissions, which in turn affected the carbon price [7, 19]. It is well known that CSI 300 Index [20], representing the overall situation of the A-share market, reflects China's economic conditions; while the Index, representing the performance of the global stock market, reflects international economic conditions. Therefore, we select the CSI 300 Index and the $S\&P$ 500 Index as indicators to evaluate domestic and international economic conditions in China.

2) The impact of financial market on carbon price

Volatility in financial markets affect interest rates and exchange rates, which in turn affect the corporate behaviors. Changes in corporate behaviors have a direct impact on the demand for carbon emissions and ultimately the price of carbon [21–23]. The Shanghai Interbank Offered Rate (Shibor) serves as a benchmark interest rate in China. Since the international carbon market is predominantly influenced by European and American markets, we select Shibor along with EUR/CNY exchange rate (exchange rate between the Euro and the Chinese yuan) and USD/CNY exchange rate (exchange rate between the United States dollar and the Chinese yuan) as indicators to evaluate the influence of financial markets.

3) The impact of international carbon market on carbon price

The European Union's Emissions Trading System (EU ETS) is the largest and most mature carbon market globally [24]. European Union Allowance (EUA) means the tradable unit under the EU ETS, and the EUA futures prices are indicative of the global carbon price trends and have an influence on China's carbon prices. We select the EUA futures prices as an indicator to assess the international carbon market.

4) The impact of fossil fuel price on carbon price

Greenhouse gas emissions primarily stem from coal, oil, and natural gas, so fluctuations in these prices can influence carbon emissions in the domestic energy market [25]. Changes in energy price affect people's energy consumption, which in turn alters carbon emissions and the demand for carbon allowances, ultimately impacting carbon price. As usual, the closing price of thermal coal serves as an indicator for the coal market, the spot price of DaQing crude oil represents the oil market, and the market price of LNG indicates the natural gas market. Therefore, we focus on these three fossil fuel price indicators to evaluate their effects on carbon price.

5) The impact of climate conditions on carbon price

Extreme weather events can escalate electricity consumption, leading to increased carbon demand and, consequently, higher carbon emissions that directly affect carbon price [26]. In China, average temperatures and Air Quality Index ($\overline{AQI}$) levels are considered indicative of the climate environment. We select daily average temperatures and AQI data from 31 provincial capitals and municipalities (excluding Hong Kong, Macau, and Taiwan) as metrics for assessing the climate environment.

6) The impact of other factors on carbon price

Governments around the world are promoting the development of the new energy sector [27]. The development of new energy sectors reduces the consumption of fossil fuels and affects the carbon price. The China New Energy Index tracks listed companies' performance in the new energy sector and is a key indicator of China's energy progress.

In the big data era, mobile equipment's generate massive amounts of data. High search volumes for terms like "low carbon", "carbon emissions", and "carbon trading" reflect public and business interest, correlating with carbon price [28]. Thus, the search indices for "low carbon", "carbon emissions", and "carbon trading" are selected as indicators to evaluate search data.

B. Data Acquisition and Key Factors Identification

We select CEA as the indicators of carbon price and establish a dataset of 518 pricing dates, which is shown in Fig. 1. All data is sourced from Wind Database, Choice Database, Weather China Website, and Baidu Search Index.

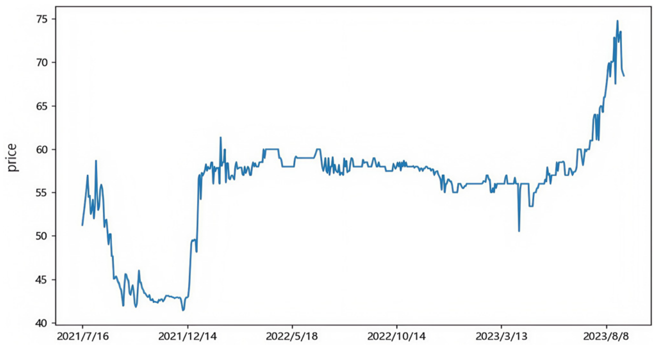

Fig. 1. China's Carbon Emission Allowance (CEA).

Table 1. Correlation analysis of influencing factors

variable	Carbon trading search index	degree of correlation
The CSI 300 index	-0.704	Significant negative correlation
S&P 500	-0.340	Low-degree negative correlation
Shibor	-0.393	Low-degree negative correlation
euro exchange rate	0.013	Weak positive correlation
dollar currency rate	0.556	significant positive correlation
EUA futures price	0.526	significant positive correlation
Thermal coal closing price	-0.029	Weak negative correlation
DaQing crude oil spot price	0.417	Low-degree positive correlation
Market price of LNG	-0.318	Low-degree negative correlation
Daily Average temperature	0.259	Weak positive correlation
AQI	0.138	Weak positive correlation
China Securities New Energy Index	-0.697	Significant negative correlation
Low carbon search index	-0.034	Weak negative correlation
Carbon emissions search index	-0.450	Low-degree negative correlation
Carbon trading search index	-0.290	Weak negative correlation

Based on the CEA price dataset, we analyze the correlation between each influencing factor and carbon price, then identify the key influencing factors utilizing Pearson's correlation coefficient. We categorize 15 factors into six groups which are shown in Table 1. The data indicates that the CSI 300 Index, USD/CNY exchange rate, EUA futures price, and the China Securities New Energy Index exhibit a significant correlation with carbon price so the four highly correlated factors are chosen as the model inputs, along with five fundamental attribute data of the carbon market, including opening price, closing price, highest price, lowest price, and trading volume. So, a total of nine variables will be applied to AAXL models.

IV. THE DESIGN OF FORECASTING MODEL AALX

A. ARIMA

ARIMA, or auto-regressive integrated moving average [29, 30], is a traditional time series model used for time series forecasting. The general form of an ARIMA model is ARIMA(p, d, q), where p is the order (number of time lags) of the autoregressive model, d is the degree of differencing (the number of times the data has had past values subtracted), q is the order of the moving-average model. The model can be expressed as

$$\left(1 - \sum_{i=1}^{p} \alpha_i L^i\right)(1 - L)^d Y_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\epsilon_t$$

where L is the lag operator, α_i are the parameters of the auto-regressive part of the model, θ_j are the parameters of the moving average part, and ϵ_t is a white noise error term.

The differencing operation is used to remove trends and seasonality, making the series stationary. Once the series is stationary, an ARIMA model can be fitted to the data to predict future values based on past observations and errors. ARIMA models are widely used in economics, finance, and other fields where time series data is prevalent [31].

B. ACNN

ACNN (Attention-based Convolutional Neural Networks) [32] are a class of neural networks that incorporate attention mechanisms into CNN (Convolutional Neural Network) architectures to enhance the model's ability to focus on relevant features in the input data. This integration allows ACNNs to dynamically weight the importance of different inputs.

The attention mechanism in ACNNs can be defined by a scoring function that calculates the relevance of different features. A common approach is to use a dot-product attention, which can be represented by the following equation:

$$score(x, y) = \frac{x^\top y}{\sqrt{d}}$$

where x and y are the feature vectors, d is the dimensionality of the vectors, and $x^\top y$ denotes the dot product of x and y. This scoring function outputs a scalar that indicates the level of attention that should be paid to the feature represented by y with respect to x.

The attention-weighted feature representation is then computed by applying a softmax function to the scores to obtain attention weights, which are used to weight the features before they are passed to subsequent layers:

$$\alpha_i = \frac{exp\left(\text{score}(x, y_i)\right)}{\sum_j exp\left(\text{score}(x, y_j)\right)}$$

$$\text{weighted\_feature} = \sum_i \alpha_i y_i$$

where α_i is the attention weight for the i-th feature, and weighted_feature is the resulting feature representation after applying attention.

C. LSTM

Long Short-Term Memory (LSTM) [33] networks are a special kind of Recurrent Neural Network (RNN) designed to remember information for long periods. They are particularly effective for tasks like time series prediction and natural language processing. LSTM mitigates the vanishing gradient problem by using a gating mechanism that controls the flow of information.

The LSTM unit consists of a cell state C_t, an input gate i_t, a forget gate f_t, and an output gate o_t. These gates allow LSTM to selectively keep or discard information, capturing long-term dependencies and making it a powerful tool in deep learning for sequence data.

D. XGBoost

XGBoost (eXtreme Gradient Boosting) [34] constructs an ensemble of regression trees in a stage-wise manner, with each tree addressing the residuals of the previous ones. XGBoost includes regularization to mitigate over-fitting, making it suitable for diverse data challenges.

The objective function in XGBoost combines training loss and regularization:

$$obj(\theta) = L(\theta) + \Omega(\theta)$$

where $L(\theta)$ is the loss function, and $\Omega(\theta)$ is the regularization term. The regularization term is:

$$\Omega(\theta) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

here, T is the number of leaves in the tree, w represents the leaf weights, and γ and λ are regularization parameters.

E. AALX

This paper introduces a model called "ARIMA integrated with ACNN-LSTM and XGBoost" (AALX), an integrated forecasting model that combines ARIMA for time series analysis, LSTM for machine learning, and XGBoost for ensemble learning, along with an Attention-Mechanism-based CNN for feature extraction. Addressing closing price of CEA, the model is designed to predict future carbon price, with the concise forecasting process as shown in Fig. 2, and specific forecasting process detailed in Appendix.

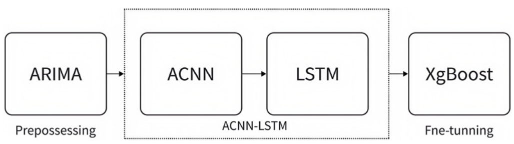

Fig. 2. Forecasting process of AALX.

V. Experimental Design and Result Analysis

A. Experimental Design

The dataset consists of opening price of CEA, closing price of CEA, highest price of CEA, lowest price of CEA, trading volume of CEA, CSI 300 index, USD/CNY exchange rate, EUA futures price, and the China Securities New Energy Index. We select TensorFlow to deploy forecasting models, utilizing the Adam optimizer for better hyper-parameters. The data is divided into a 70: 30 split for training and testing. Before training, the CEA series are first preprocessed by ARIMA model, the new series is then put into the ACNNLSTM, whose output is then fine-tuned by the XGBoost model to obtain the final prediction. Comparing the prediction against the actual closing price of CEA, we use MSE, RMSE, MAE, and R-squared values as the indexes to quantify the effectiveness of AALX model. Here is a concise summary of the forecasting process of AALX, with the specific forecasting process detailed in Appendix.

(1) Preprocessing: The original closing price series are first subjected to ARIMA model for stationarity testing, which reveals non-stationarity. After first-order differencing as shown in Fig. 3, the series becomes stationary. After trying several ARIMA models based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) shown in Fig. 4. we finally determined that ARIMA(2,1,0) is the best model for the carbon price series. After preprocessing, a new series and a residual sequence are generated. Subsequently, the obtained sequences were merged with other data (highest price of CEA, lowest price of CEA, trading volume of CEA, etc) as input variables for the machine learning model. The results of preprocessing are shown as Fig. 3 and Fig. 4:

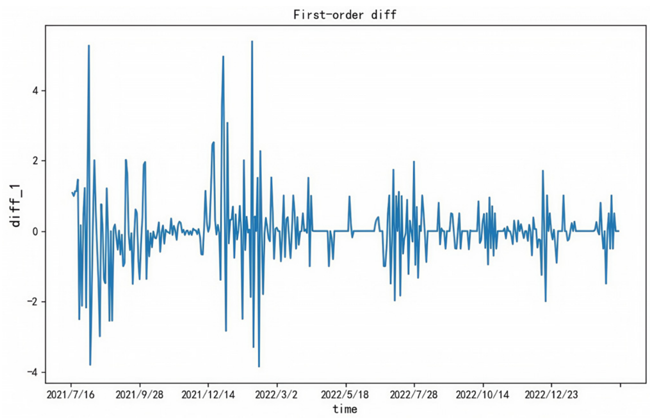

Fig. 3. First-order differenced data series.

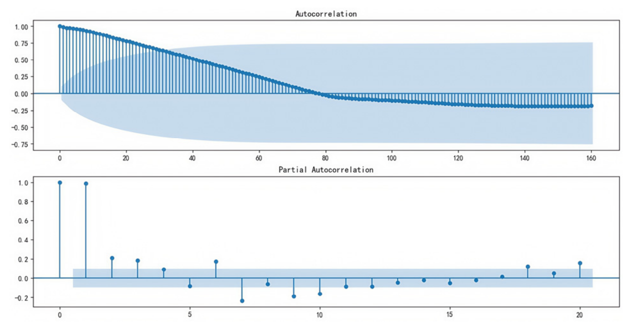

Fig. 4. Autocorrelation and partial autocorrelation plots.

(2) Training: The output series with CSI 300 index, USD/CNY exchange rate, etc. is fed into a sequence-to sequence CNN-LSTM model with Attention-Mechanism.

The Attention-Mechanism-based CNN serves as the encoder, capturing features with its multi-scale convolutional kernels while the LSTM acts as the decoder, adept at characterizing time series properties. To learn the important local features of data, the sequence is first put in the ACNN. The sequence is then proceeds to the LSTM for carbon price forecasting with a 10–day lag window, enabling comprehensive temporal learning.

(3) Fine-tuning: After decoding, the carbon price series predicted by the machine learning model is further input into the XGBoost model. XGBoost, an ensemble of regression trees, refines predictions through iterative modeling. Finetuning by XGBoost is able to capture additional information and patterns of data, and ultimately yield the final prediction.

B. Result Analysis

To demonstrate the effectiveness of AALX, this paper also employs the foundational modules constituting AALX as comparative benchmarks. The results are shown as Figs. 5–8:

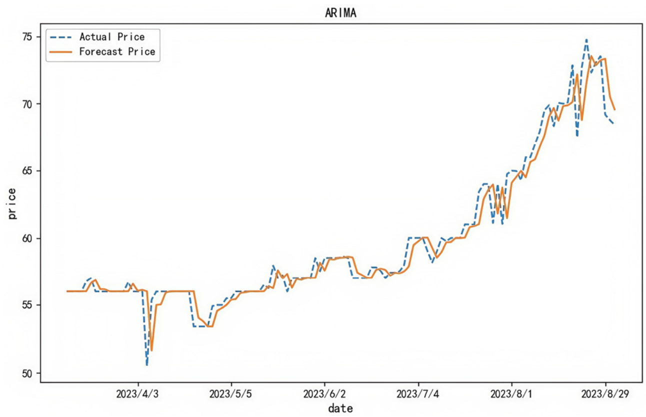

Fig. 5. ARIMA Model forecasting results.

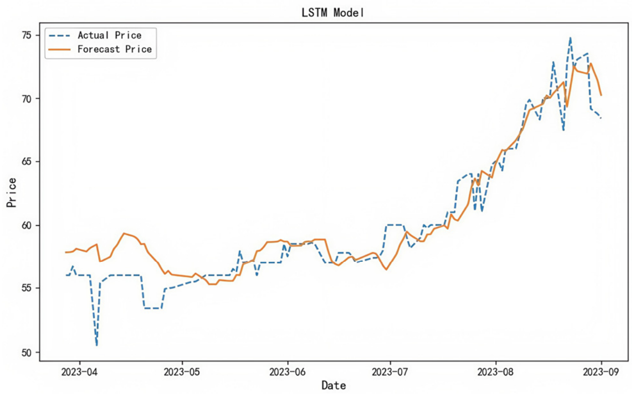

Fig. 6. LSTM model forecasting results.

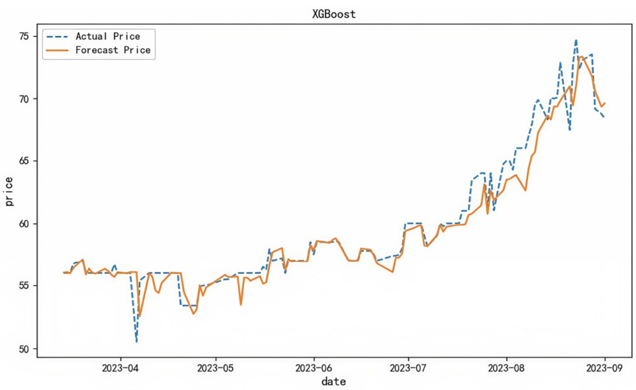

Fig. 7. XGBoost model forecasting results.

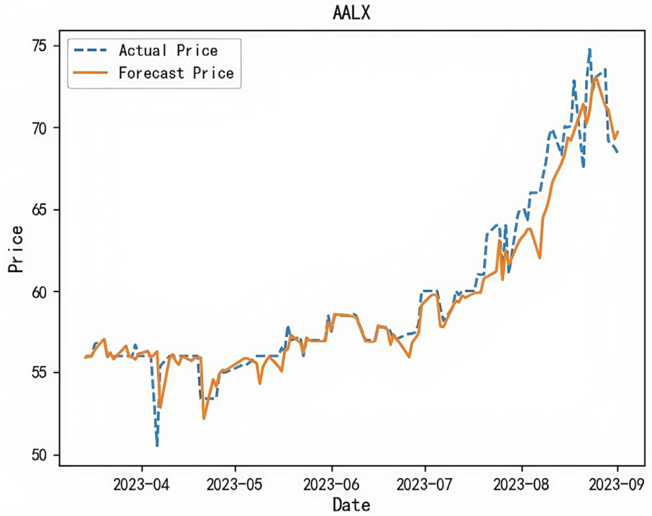

Fig. 8. AALX Model Forecasting Results.

The performance of these models is assessed by MSE, RMSE, MAE, and R^2. It can be shown by the Table 2 that AALX outperforms the other three in terms of MSE, RMSE, etc, indicating its superior capability to reduce prediction errors. Furthermore, the R^2 value of AALX shows its higher prediction accuracy over baseline models, with a 3% improvement over LSTM, a 1% improvement over ARIMA, and a 0.2% improvement over XGBoost. The performance indicators for the models are shown in Table 2.

Table 2. Model performance indicators

	MSE	**RMSE**	**MAE**	**R^2**
ARIMA	1.80015	1.34170	0.80205	0.93624
LSTM	2.13522	1.46124	1.19099	0.91878
XGBoost	1.52636	1.23546	0.72227	0.94617
AALX	1.47383	1.21402	0.69126	0.94802

VI. Conclusion

Focused on the carbon price in China, we start with a theoretical analysis of the China carbon price influencing factors, then employs Pearson correlation coefficients to identify the key influencing factors of carbon price. We introduce a combined model called AALX, which have not been applied to carbon price forecasting, to forecast CEA, which is an indicator for carbon price. The effectiveness of AALX is evaluated using MSE, RMSE, etc, revealing that AALX model demonstrates superior accuracy, as well as highlighting efficacy and practicality over other baseline models.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Ailing Gu conducted the research; Chengtuo Lie, and Jiayan Lin analyzed the data; Yu Hao wrote the paper. All authors had approved the final version.

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