Forecasting European Union Electronic Trading Systems Phase 4 Spot Prices Using Data-Driven Hybrid Deep Learning Models: Integrating Energy and Market Activity as Controls

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ETHICAL DECLARATIONS

Conflict of Interest

All the authors hereby state that there is no conflict of interest with the content of this article, both in terms of academic and professional capacity. It is to affirm that the work is not submitted anywhere else other than this journal.

Ethical Approval

The entire research process is in line with our institutional research ethics policy. We declare that all ethical standards are met and complied with in true letter and spirit.

Informed Consent

The study is based on secondary data so no consent was required.

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Abstract

Amid the focus on climate change mitigation this study explores carbon market forecasting. This study uses a hybrid forecasting framework that integrates Empirical Model Decomposition, Bidirectional Long Short-Term Memory (BiLSTM) network, and attention mechanism to enhance the predictive performance of carbon spot prices within the European Union (EU) Emissions Trading System (ETS). The model decomposes the nonstationary carbon prices to multiple Intrinsic Mode Functions (IMF) representing each distinct frequency component. The forecasting at IMF level enables learning of temporal dependence and volatility. The final model reconstructs the signals to present overall prediction. The multiple iterations that include a selection of macroeconomic variable led to the final Root Mean Square Errors (RMSE) value of 4.59 which shows that the BiLSTM outperforms a conventional Long Short-Term Memory (LSTM) setup. This study also improves the model by including exogenous macroeconomic variables and policy shocks to enhance predictive accuracy. Shapley Additive Explanations (SHAP) analysis also identified the important features and variables. The visualized confidence interval confirms the reliability of the forecasts. The findings of the study highlight the effectiveness of integrating signal decomposition with deep learning and inclusion of exogenous factors. This study offers practical insights for regulators and researchers who are engaged in the emissions market and climate finance.

Keywords: carbon markets; self-attention mechanism; forecasting uncertainty; European markets; SHAP analysis

1. Introduction

Globally there is an urgency of climate change mitigation. It has elevated exploration of carbon pricing markets and mechanisms. The European Union Emissions Trading System (EU ETS) is leading in this market based environmental regulations. The structure of carbon markets is evolving in terms of complexity and interconnectedness which is allowing market forces to change the carbon pricing freely. The free movement of carbon prices had necessitated the forecasting of carbon allowance prices that can provide strategic enablement for regulators, investors and industries in carbon – intensive supply chains. Firms need to have an accurate assessment of carbon prices to maintain their predictable control on the cost of production to maintain their competitive advantage in the global market. Thus, an accurate carbon price forecast is required not only to make informed financial decisions but rather to hedge strategies in accumulating carbon credits or to invest in low-carbon technologies. This helps to reinforce climate policy and ensure regulatory adaptability in the expanding markets even under volatile conditions (Zhang & Wu, 2022; Zhu et al., 2023).

Carbon prices are volatile, cyclic, and nonlinear in nature (shown in Figure 1). The antecedents of carbon prices range from energy market fundaments to macroeconomy policies and geopolitical disruptions (Byun & Cho, 2013; Feng et al., 2011). Recently, there has been a rapid development in making efficient forecasting models. It started with econometric models such as Autoregressive Integrated Moving Average – Generalized Autoregressive Conditional Heteroskedasticity (ARIMA-GARCH), regime-switching, and cointegration-based approaches (Benz & Trück, 2009; Chevallier, 2011b). These models were useful in capturing the memory in time like stationarity and linear inertia. However, these models lacked the ability to capture the multifractal and chaotic nature of carbon pricing dynamics. As a result of this there has been a growing shift toward the use of machine learning (ML) and hybrid forecasting models that can account for nonlinearity and regime change (Fan et al., 2015; Zhu et al., 2021).

While assessing carbon markets, two principal mechanisms have been developed globally. They are carbon taxes and cap-and-trade systems (also known as emission trading schemes (ETS)). This study is exploring the ETS instruments as there are several market-based carbon pricing indices available that are used for emissions trading performance. The popular indices are EU ETS EUA (European Union Allowance) sport price, RGGI (Regional Greenhouse Gas Initiative in northeastern United States of America (USA)) price index, CCA (California Carbon Allowance under western climate initiative), and the China National ETS benchmark. Among these indices this study has selected the EU ETS EUA sport price (shown in Figure 1) which is the most liquid, transparent, and widely studied index. This index includes 10,000 installations in 27 EU countries and three non-EU countries (Ellerman et al., 2010; World Bank, 2023). This market is popular because of multiple policy interventions like Market Stability Reserve, European Green Deal, and Carbon Boder Adjustment Mechanism. These have led to regulatory maturity and make it a forward-looking signal of carbon risk as highlighted in Figure 1.

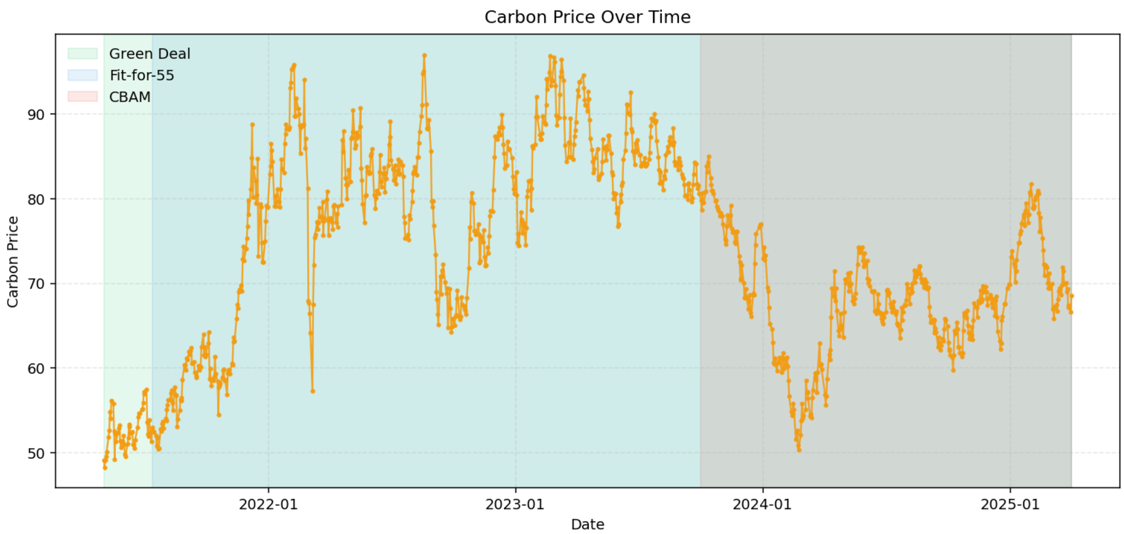

Figure 1 – Trends in EU ETS EUA Carbon Spot Price with Regimes

Here we discuss some economy stylized faces of EU ETS price formation. This EUA price indicator is closely linked with energy prices where an increase in prices leads to EUA demand. Phase 4 tightening, MSR reforms led to persistent structural breaks and long run price changes. This indicator can show crisis-driven spikes, policy shocks, and long-term volatility.

This study adds to the evolving discourse in the domain of forecasting carbon prices and use of advanced machine learning models by developing a hybrid forecasting model. This forecasting model integrated Empirical Mode Decomposition (EMD) with the Bidirectional Long Short-Term Memory (BiLSTM) model that is augmented by attention mechanisms. The EMD method is used to decompose the nonstationary carbon price data into multiple Intrinsic Model Functions (IMFs) that capture the multiple forms of distinct frequency and volatility in the data. This decomposition method enhances the signal-to-noise ratio which is required as expected from the heterogenous time series periodicities in the data (shown in Figure 1) (Zhang et al., 2017; Zhu et al., 2017). In this context, each of the IMF is modeled using the BiLSTM attention network which has enhanced interpretative capability to capture both short-term dependencies and complex temporal dynamics.

To accommodate the integrated nature of carbon markets, this model also adds exogenous fundamentals. These fundamentals constitute variables from macroeconomics, energy, and policy domains. This study deployed variables like Brent Crude Oil Prices, EUA Trading Volumes, Europe Average of Geopolitical Risk Index (GPR), and Europe Harmonized Consumer Price Index (CPI). Government policy development is also incorporated using binomial dummies like EU Green Deal (2019), Fit for 55 Package (2021), and Carbon Border Adjustment Mechanism (2023). The inclusion of these variables helps to make a multi-layered structure of carbon pricing dynamics and the selection of the variables are merited from literature (Hua et al., 2025; Huang et al., 2021).

1.1. Positioning, Novelty, and Contribution

The use of rigorous modeling and empirical validation has led this study to offer several novel contributions. Firstly, it has used a robust and hybrid deep learning framework that can capture nonlinear and nonstationary features of carbon spot prices in Europe. Secondly, this study demonstrated how multivariate explanatory fundamentals and policy shocks can be embedded into the complex decomposed forecast architecture. The joint decomposition of predictors and target variables are contributions of this study. This study also proposed policy dummies that are rare in prior models. Thirdly, the models used are not only evaluated in sample performance but also forecasting accuracy across multiple IMFs. All these actions culminate into narrow confidence intervals and low Root Mean Square Error (RMSE). Broadly speaking, this model has developed a complex but interpretable carbon price forecasting model.

This study has identified several gaps in the carbon price forecasting discipline. Firstly, this study bridges the methodological divide between signal decomposition and deep learning. Zhang et al. (2023) used multivariate decomposition without policy regimes.

It uses Empirical Mode Decomposition and Bidirectional Long Short-Term Memory which is enhanced with the attention mechanism in the form of policy dummies. Previous studies have used these models separately like EMD with Sector Vector Regression (SVR) (Zhu et al., 2017). There are few studies that combined these with attention to enhance temporal focus cross multiresolution signal. Secondly, empirical studies mostly focus on the univariate forecasting for the sake of ease in future forecast projection (Wang et al., 2023). This study enriches the model using a rich set of exogenous variables like macroeconomic indicators, energy market signals, geopolitical risks, and policy events. The results showed that this hybrid model performs better than benchmark forecasting models. And results are based on the structured economic transmission mechanisms across temporal scales which pointed to heterogenous drivers of carbon prices across decomposition.

Following the introduction, this study provides a literature review regarding the relevancy of attention mechanisms used in forecast models. Section 3 provides details on the estimation methods. Section 4 provides the results and aligns it with the aim of the study in the discussions. Section 5 concludes the study with theoretical and practical policy implications.

2. Literature Review

Forecasting time series data, especially carbon prices, has received significant scholarly attention in past years mainly because of the development of complex models on the one hand and increasing importances of carbon emissions trading schemes amid changing climate policies on other hand. Due to its size and liquidity, the European Union Emissions Trading System (EU ETS) has been focused on empirical and methodological innovation. In this section, this study synthesizes key contributions in carbon price modeling and discusses the evolution of forecasting models form econometric frameworks, machine learning, and hybrid approaches that are used in encompassing the complex nature of carbon markets.

2.1. Traditional Econometric Forecasting Models

Early studies used the linear time series models to forecast. These were based on variations of data like Autoregressive Integrated Moving Average (ARIMA), variance of the data like Generalized Autoregressive Conditional Heteroskedasticity (GARCH), or based on multiple endogenous variables like Vector Autoregression (VAR) models. There are studies available that have used these models to estimate carbon prices. Benz and Trück (2009) used the GARCH model on EU ETS Phase 1 and 2 data and concluded that there is volatility clustering. Chevallier (2011b) used econometric cointegration techniques to link carbon prices with energy markets as fundaments. The study concluded that carbon prices must not be forecasted in isolation to macroeconomic shocks. Although these models had high interpretability, they also had limited ability to handle nonlinearities, structural breaks, and volatility regimes. This study had added the lag of the dependent variable and the variance of the dependent variable as potential exogenous variables which can help the model to pick up the variations.

2.2. Regime-Switching Nonlinear Models

The Markov Regime-Switching and other threshold based models were adopted within the literature to overcome the limitations of the linear models because of its nonlinear estimation capabilities (Creti et al., 2012). These models can include structural changes and regulatory shocks as exogenous variables in order to account for sudden breaks in the data. While they are able to capture the market asymmetries, prior knowledge about the data distribution and market events are required to make a robust model as these models are sensitive to outliers (Guidolin, 2011).

2.3. Machine Learning and Deep Learning Forecasting Models

The recent development in the domain of data science and machine learning has led to the evolution of machine learning and deep learning forecasting models. These models can capture complex patterns. Models like Support Vector Regression (SVR), Gradient Boosting Machines (GBM), and Random Forests (RF) have performed sufficiently well (Zhu et al., 2017). The Long Short-Term Memory (LSTM) model and its extensions such as Bidirectional LSTM (BiLSTM) have been successful in modeling temporal dependences (non-stationary behavior) inherent in carbon markets (Huang et al., 2021). The LSTM based models can adapt long-term dependencies and temporal changes even though they do not need any stationarity adjustments. Since these models are adaptable, their performance can be further enhanced by integrating with other models or processes. Previously, a study by Zhu et al. (2017) improved the model by decomposing the signal before forecasting it. The signal decomposition process is known as Empirical Model Decomposition (EMD). Zhu et al. (2017) used it with SVR to forecast the EU ETS prices. The results showed that this hybrid model improves the noise reduction process and makes models interpretable.

2.4. Hybrid and Decomposition Models of Forecasting

The advantage of machine learning models is that they can be integrated with other models to make them hybrid. Several models have been developed and used in literature that helped in improving the forecasting performance. A study by Zhang et al. (2023) had used ET-MVMD-LSTM to forecast carbon pricing. The resultant model showed superior performance in forecasting carbon prices. Recently, attention-based mechanisms are used in the LSTM models that can selectively focus on relevant parts of the time series data (Duan et al., 2023; Luo et al., 2022; Wang et al., 2023). These advanced models have shown superior interoperability and reduced overfitting. Such characteristics are suitable in the context of volatile financial environments.

2.5. Inclusion of Exogenous Factors and Policy Shocks

This study has gone beyond methodological enhancement to include the macroeconomic fundamentals and policy shocks. Literature has also pointed out the merits of using macroeconomic, geopolitical, and policy related fundamentals in order to improve the carbon pricing models (Chevallier, 2011a; Fragkos & Fragkiadakis, 2022; Mengistu et al., 2019). Studies have used policy events like the European Green Deal and CABM initiative to learn the patterns in carbon pricing (Almondo, 2025; Böning et al., 2023; Weishaar, 2023). Other indicators like geopolitical risk (Lau et al., 2023), inflation, and energy prices have also improved the performance of the carbon price forecasting models. It has received growing attention while linking carbon prices with macroeconomic determinants. Macroeconomic factors play an important role within the markets that are highly integrated and mature in terms of policy reforms. Crude oil price as a fundamental energy cost has close links with energy consumption, resource substitution effects, and other speculative activity. Higher oil prices lead to higher production costs which could, in turn, alter carbon emissions in the absence of low-carbon alternatives (Soliman & Nasir, 2019).

Greater trading volume typically enhances market liquidity, reduces bid-ask spreads, and facilitates faster price discovery. This effect can help stabilize price trends in response to market sentiments (Chevallier, 2011c). This trading creates a feedback loop that ensures the market is not only policy driven but also market responsive. Consumer prices depict the cost of living and cost of products and can lead to an increase in cost of compliance to carbon abatement investments. Inflation may lead to a fall in the real value of carbon prices which will reduce the deterrent of emissions permits (Martin et al., 2014). Hence, the performance of carbon markets may undermine in times when there is high inflation.

Geopolitical risk is the least explored determinant of carbon pricing. It measures events like war, sanctions, and policy instability which may disrupt global supply chains. In these times, firms might be forced to shift fuel mix and leave long term plans. The uncertainty regarding environmental regulation continuity also prevails. An empirical increase in geopolitical risk leads to carbon market volatility. As a result, the process of clean energy transition is dampened (Jiang et al., 2024). Duan et al. (2021) estimated the asymmetric effects of risks on carbon prices whereby negative shocks are stronger using the fuel-switching theory. Ji et al. (2020) compared the Covid-19 risks on asset prices showing that it causes cross market contagion effects. In the case of climate policy events, major events do determine how markets will perform. The events that are selected in this study are the European Green Deal, Fit-for-55, and Carbon Border Adjustment Mechanism (CBAM). They have a direct effect on EUA prices. Empirical studies have shown that these policy interventions have created structural breaks and regime shifts in the carbon price series (Bayer & Aklin, 2020; Verde & Borghesi, 2022).

Existing studies on carbon price forecasting reveal critical gaps. Within the high frequency domain the ARIMA and GARCH models struggle to observe multifractal behaviors (Zhan & Li, 2025). Early developments tried to hybridize ARIMA models within machine learning using support vector machines which can address nonlinear predictions (Zhu & Wei, 2013). These models still lack in observing sudden policy shifts which require deep learning (Ren et al., 2025). While using empirical data models cannot predict new breaks and pure LSTM models tend to overfit (Yu et al., 2024). Empirical studies also focus on predictive performance without economic transmission mechanisms and function as black-box predictors. They do not have economically interpretable systems. The overfitting of LSTM frameworks is often under-discussed. To address these limitations, hybrid models are used to integrate signal decomposition and nonlinear forecasting methods. An EMD model can isolate trends from high frequency data and has shown its effectiveness (Zhu et al., 2018).

Conclusively, literature has pointed out several aspects discussed in different studies. This study is forming the hybrid model that integrates the power of each method to improve forecasting ability. The first is the decomposition of carbon price signals using EMD. The second is using BiLSTM with attention network and the third is the inclusion of explanatory variables and policy shocks. This tripartite extension of forecasting model led to an expectation of improved accuracy and an interpretation of European carbon price forecasting. Since this study performed forecasting using attention mechanisms, the key features (specific lags of independent variables) and variables are identified by this study. Hence, this study provided a better performing forecasting model with interpretability of attention mechanism that assists policy makers to anticipate future movements as well as increasing regulatability.

3. Methodology

This study is designed to forecast the European Union Allowances (EUA Phase 4) using a hybrid model that combines Empirical Mode Decomposition, Bidirectional Long Short-Term Memory networks, and attention mechanisms. In this section the methodology is structured to explain data selection, processing, signal decomposition, and predictive modeling.

3.1. Theoretical Framework and Hypothesis Development

There are two theories that provide the foundation of the study. From environmental economics, Cap-and-Trade Theory explains the changes in EUA prices because of allowance scarcity, regulatory tightening, and compliance demand (Fell & Morgenstern, 2010; Newell et al., 2014). From energy economics, Fuel-Switching Theory explains how energy producers switch between energy sources to mitigate the costs. The changes in energy prices then alter the EUA demand (Bunn & Fezzi, 2007; Delarue et al., 2008). This theory further implies that energy price fluctuations have an asymmetric transmission effect to carbon demand. The shift between coal and gas in response to fuel price depends on emission intensity and marginal costs that explains substation effect. This transmission also has temporal delays due to contract bindings, hedging positions, and production adjustments lags. This advocates the use of lagged independent variables. Further, since carbon prices evolve in multiple horizons defined by liquidity in short term and policy tightening in long term, so the BiLSTM attention is also theoretically consistent.

Hence the hypotheses tested by this study are:

H1: Energy market fundamentals have a dynamic influence on EUA via fuel-switching.

H2: Macroeconomic conditions, such as inflation and geopolitical risk, alter compliance costs and expectations hence they change EUA prices.

H3: Structural policy interventions are increasing EUA prices via strengthening allowance scarcity expectations and regulatory credibility.

H4: Decomposing carbon prices into multiple intrinsic modes improves the forecasting accuracy.

H5: The predictive importances of energy, macroeconomic, and policy variables are altering across frequencies of carbon prices.

3.2. Variables and Data Sources

This study has used EUA Phase 4 Spot Price as the European Carbon Price index which is EU Emissions Trading System Benchmark as the main variable that is being forecasted. The daily data is acquired from the London Stock Exchange Group (LSEG) Workspace database for the time period of March 2021 to January 2025. Other explanatory variables are discussed as follows. In the case of resource prices, Daily Brend Crude Oil Prices are used. The market size is estimated using the EUA Trading Activity Volume. Both variables are acquired from the LSEG Workspace database. The macroeconomic conditions are estimated using Geopolitical Risk where the average of Geopolitical Risk Index of European Countries are used (Caldara & Iacoviello, 2022) and further interpolated from monthly to daily frequency. The geopolitical risk index is an index resulting from an automated text search from 10 electronic newspapers. The search includes eight categories from war threats to terror acts. A similar case is with the Consumer Price Index of Europe which is acquired from International Financial Statistics in monthly frequency and later interpolated to daily frequency. Since both GPR and CPI are indicators of expectation formation, regulatory responses, and investment decisions that evolve over time rather than daily. Using their smooth form is consistent with the economic transmission mechanism. Further, the smoothing bias is addressed when the model estimates long-run components and short-term noise. The use of decomposition framework is mitigating potential distortion by isolating the frequencies. Lastly, the policy developments are included using dummy variables which are stated below. The use of multivariate input helps in incorporating the fuel-switching behavior and energy shocks.

i. *Green Deal Dummy* ("green_deal"): 1 from 2019-12-11 onward.
ii. *Fit-for-55 Dummy* ("fit_for_55"): 1 from 2021-07-14 onward.
iii. *CBAM Dummy* ("cbam"): 1 from 2023-10-01 onward.

The European Union carbon markets have seen several phases of regulation to improve the EUA price dynamics and their responsiveness to market. First is the Green Deal providing an ambitious roadmap for climate neutrality by 2050. This helped in increasing long-term policy credibility and expectations (The European Green Deal, 2019). The Fit-for-55 regime targeted 55% greenhouse gas emission reduction by 2030 and added a stringent reduction factor (‘Fit for 55’: Delivering the EU’s 2030 Climate Target on the Way to Climate Neutrality, 2021). Lastly, CBAM initiated a structural shift in EUA demand dynamics (Establishing a Carbon Border Adjustment Mechanism, 2021).

The model includes the lag of dependent variable and variance of the dependent variable to account for the volatility in the data. Also, the model uses 30-day lags for all the independent variables so that the model can be used to generate a 30-day forecast. This lag selection is motivated by economic reasoning and empirical considerations. In economic perspective, carbon markets show delayed adjustments. The energy shocks and policy signals are not instantaneous. The shorter window may overlook delayed substitution effects while longer windows may dilute relevant signals. Hence a 30-day window is used as a moderate time period to allow capturing of transmission dynamics.

3.3. Empirical Mode Decomposition (EMD) Method

This method is an alternative to the dynamic series models which can entertain nonstationary variables. EMD can decompose the nonstationary and nonlinear variables into multiple Intrinsic Model Functions (IMFs) and a residual. The purpose of IMFs is to capture the oscillations in the high frequency volatile data at different time scales (Naeem et al., 2024; Nava Morales, 2016; van Jaarsveldt et al., 2023) which can determine the policy regime shifts. The mathematical derivation of the model is as such

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + r(t)$$

Here $IMF_i(t)$ is the i^{th} Intrinsic Mode Function, and the r(t) is the residual.

EMD model is selected as it is adaptive in handling non-stationary and nonlinear data. Other models, like Variational Mode Decomposition (VMD), require data to be quasi-stationary and requires modes to be predetermined rather than estimating it from data (Dragomiretskiy & Zosso, 2014). While EEMD and CEEMDAN are complex models that use artificial noise injection, they require higher computational resources in the case of high frequency data (Colominas et al., 2014). In contrast, the EMD model preserves the original signal and ensures interpretability.

3.4. Predictive Model

Each IMF estimated in 3.2 is modeled in the BiLSTM network to capture its forward and backward temporal dependencies. The model is augmented with self-attention mechanism (Cai et al., 2022; Vaswani et al., 2017). This can help in extracting most information from the time variations in the data.

3.4.1. LSTM Structure

The use of an LSTM structure can help in capturing the volatility clustering. The LSTM units are estimated using the following equations

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right)$$

$$h_t = o_t \odot \tanh\left(c_t\right)$$

Here i_t, f_t, and o_t are the input, forget, and output gates, c_t is the cell state, and h_t is the hidden state.

3.4.2. Attention Mechanisms

The self-attention mechanisms in the model assign weights to each time step that enables the model to prioritize important inputs in the forecasting process.

$$\alpha_t = \frac{\exp\left(e_t\right)}{\sum_{k=1}^{T} \exp\left(e_k\right)}, e_t = v^T \tanh\left(W h_t + b\right)$$

Here $\alpha_t$denotes the attention weights at a given time t. and h_t is the BiLSTM hidden state.

3.5. Forecasting with Confidence Intervals and Evaluation

The forecasting is conducted at each IMF level and then overall predictions are aggregated.

$$\hat{y}_t = \sum_{i=1}^{n} \widehat{IMF}_i(t)$$

The forecasting model does not directly provide the confidence interval; this study quantifies this uncertainty by making a 95% confidence interval using standard deviation of residuals.

$$CI_t = \hat{y}_t \pm 1.96.\, \sigma_{residual}$$

The model forecasting performance is evaluated using root mean squared error (RMSE) for each IMF and final reconstructed forecasts. Visualizations are also provided.

3.6. Python Libraries

The python workflow is built using pandas, NumPy, and Matplotlib for data cleaning, mathematical operations, and plotting. PyEMD is used to decompose the data into intrinsic mode functions. Scikit-learn normalized the inputs and generated the metrics for forecast evaluation. TensorFlow Keras is used to estimate the BiLSTM model. Keras-self-attention is used to add attention layers. SHAP is used to explain the trained models to identify most attributing lag feature and important variables. Finally, the statsmodels library helped in estimating the baseline forecast models for the study.

4. Results and Discussions

This section presents the forecasting performance of the hybrid EMD-BiLSTM-attention model using a multivariate panel of explanatory variables and policy shock dummies. The model provides the forecast performance at two levels; the first is at the IMF level and the second is the reconstructed dependent variable signal level. The final reconstructed forecast also includes the 95% confidence interval.

4.1. IMF level Forecasts

Each of the seven IMFs are estimated using EMD and are then modelled separately using the BiLSTM model with self-attention. The forecast performance is measured using RMSE.

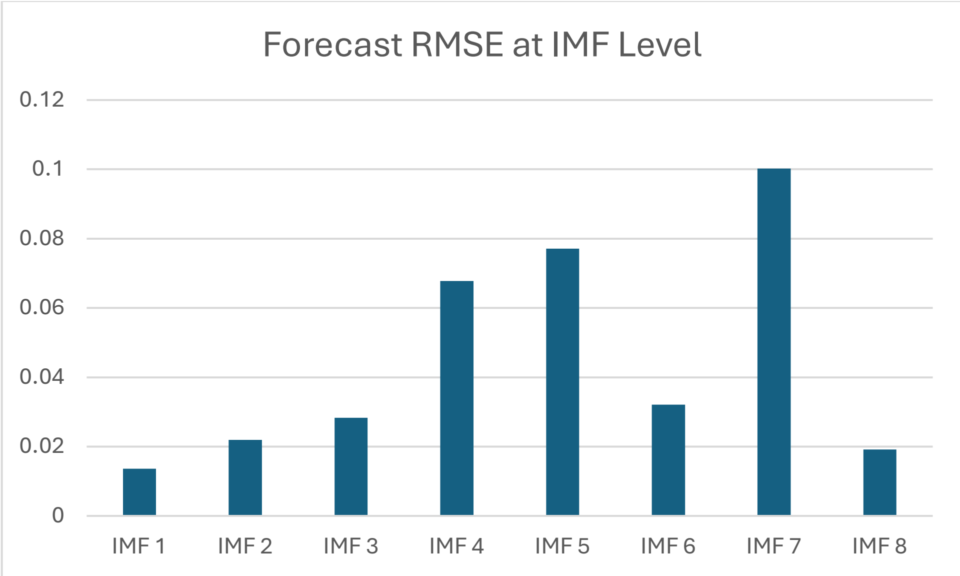

Figure 2 – IMF level estimates' forecast performance

Model	**RMSE**
Naïve (last value)	1.2677
Moving Average (k=7)	2.1031
SES	4.9172

Table 1 – Comparison with benchmark models

Figure 2 shows IMF forecasts. Here, this estimated model shows strong predictive frequency for high frequency IMFs like IMF1, IMF2, and IMF3 where the RMSE values are below 0.03. This shows the model performs well in capturing short-term volatility. The medium-term IMFs, like IMF4 and IMF5, are showing moderator forecasting accuracy where RMSE values are below 0.05. In the case of low-frequency IMFs, like IMF6 and IMF7 that represent trends and seasonality, they show high RMSE values. This might be because of slow-moving data structures which, in turn, might require appropriate amendments in future models. Finally, IMF8 has a low RMSE value. This shows that other than RMSE 4, 5, and 7, the model can forecast the signal sufficiently. Generally RMSE is highly context specific but studies on stock markets reported RMSEs to be between 1.5 to 3.0 (Lindner, 2025). This study can improve RMSE values using advanced models. Table 1 provides the benchmark forecasting performance. This study has used the Naïve model using last value and moving average model using 7 window length and simple exponential smoothing. When comparing individual IMFs with these it can be noted that individual IMFs are performing better than these benchmark models. This outcome supports hypothesis H4.

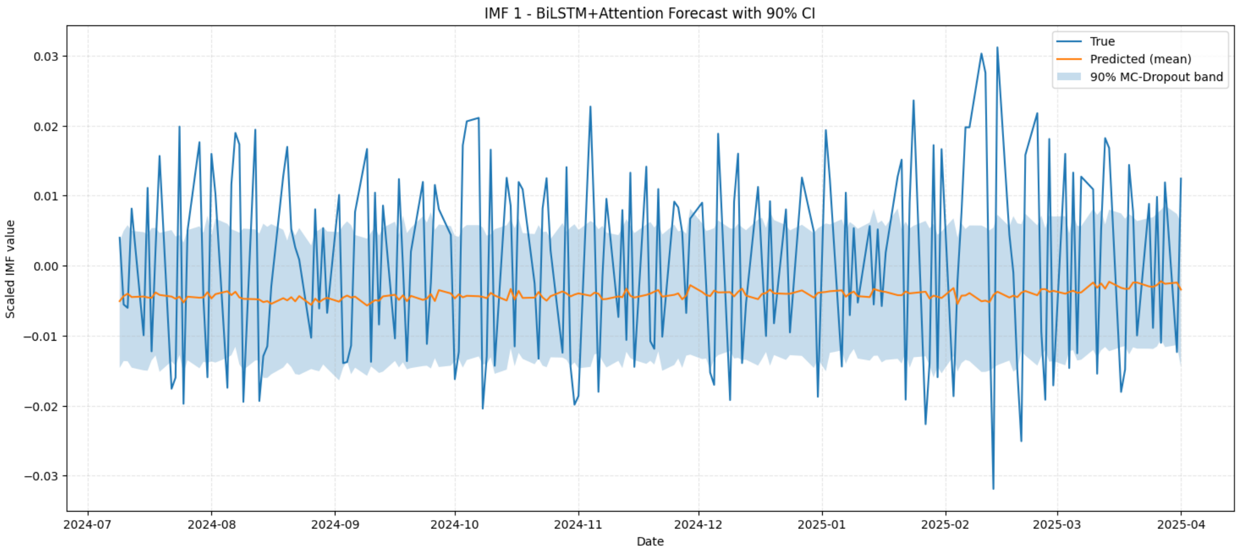

Figure 3 – Forecasting of IMF1 level

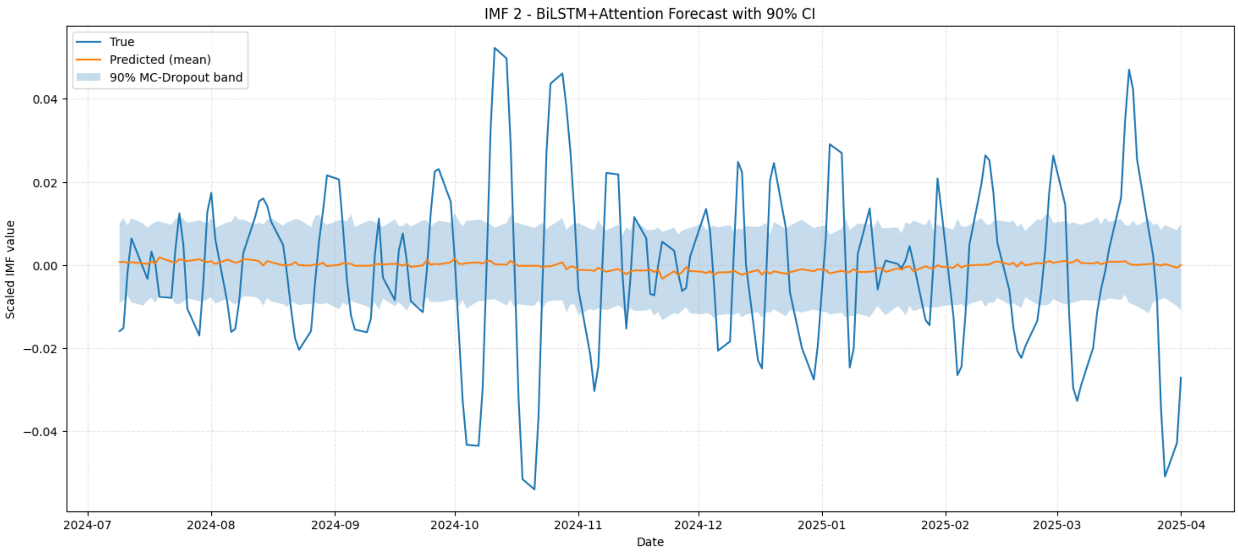

Figure 4 – Forecasting of IMF2 Level

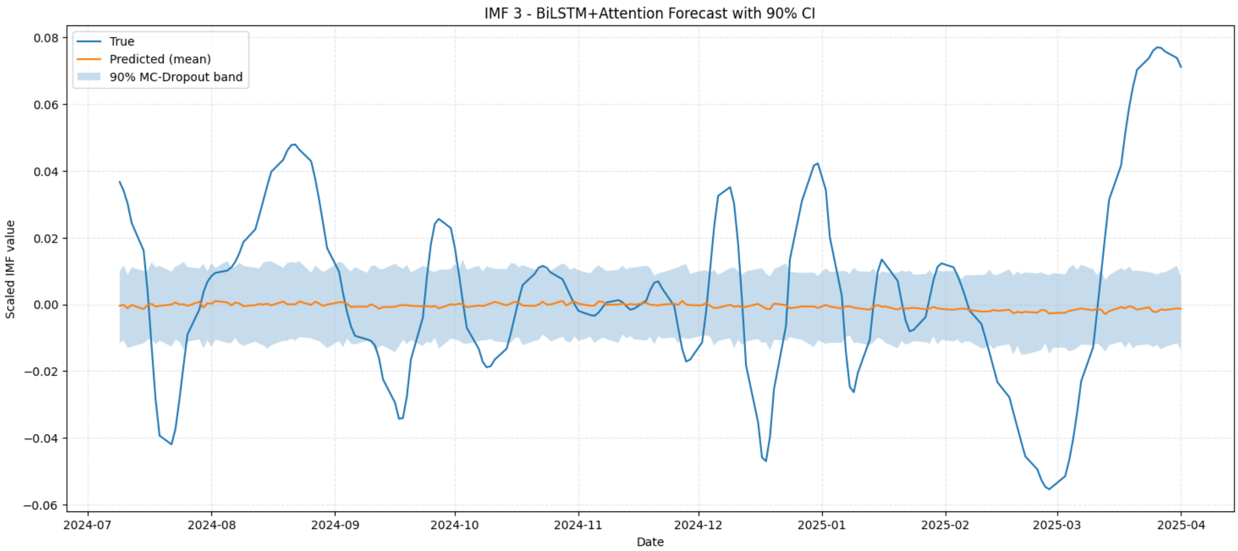

Figure 5 – Forecasting of IMF3 level

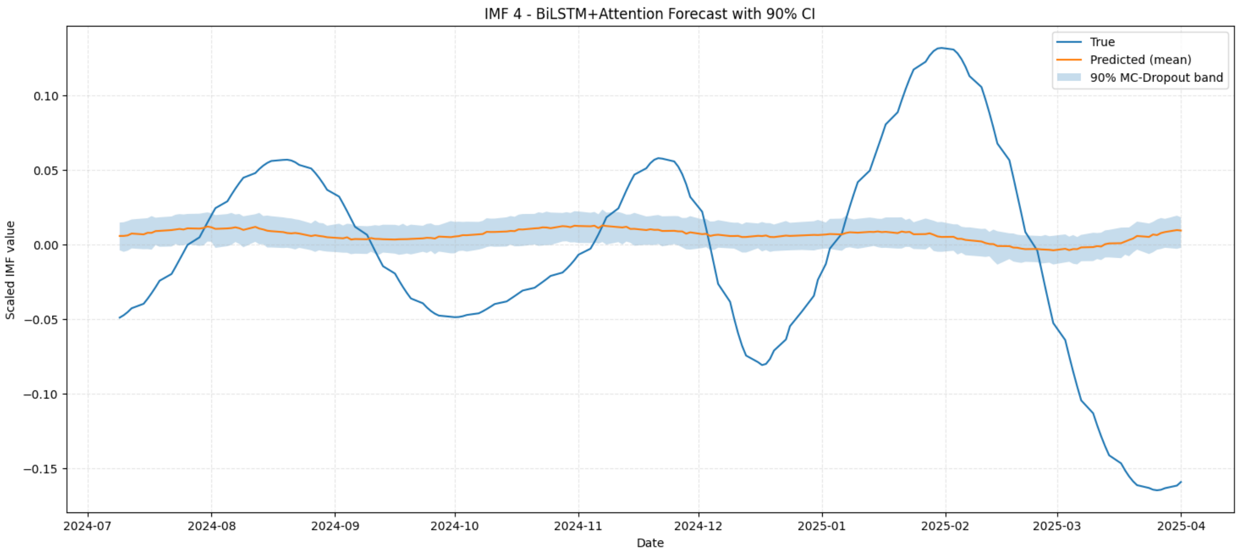

Figure 6 – Forecasting of IMF4 level

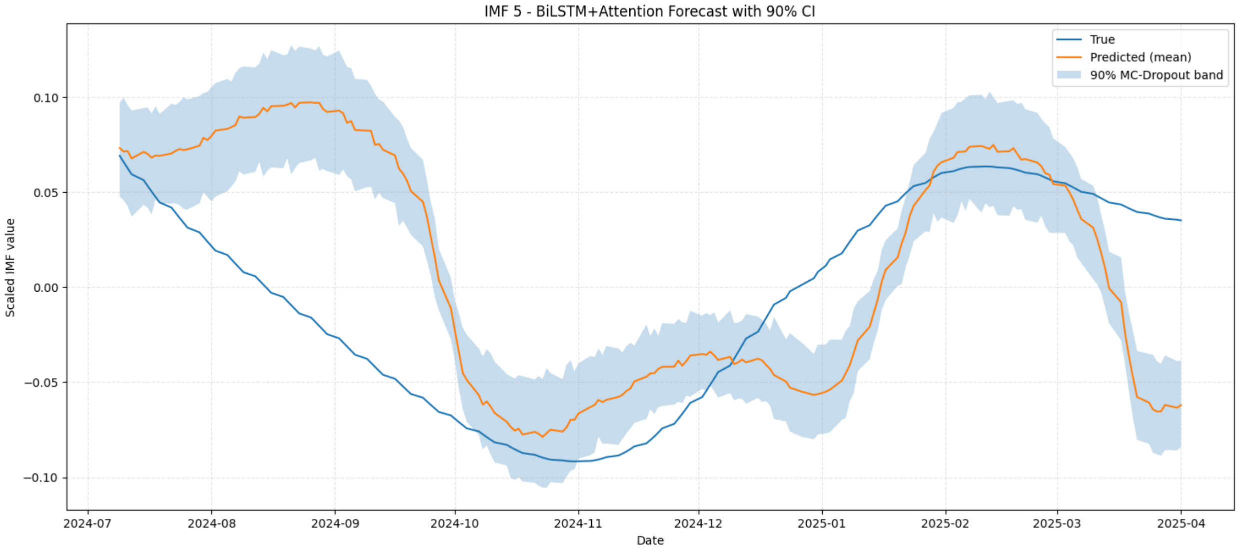

Figure 7 – Forecasting of IMF5 level

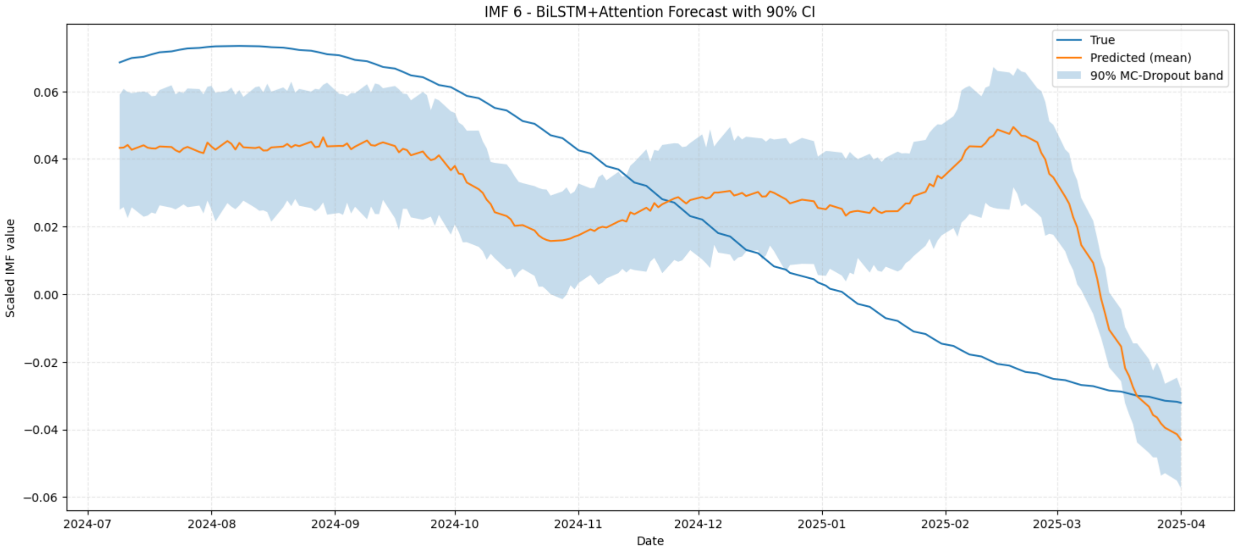

Figure 8 – Forecasting of IMF6 level

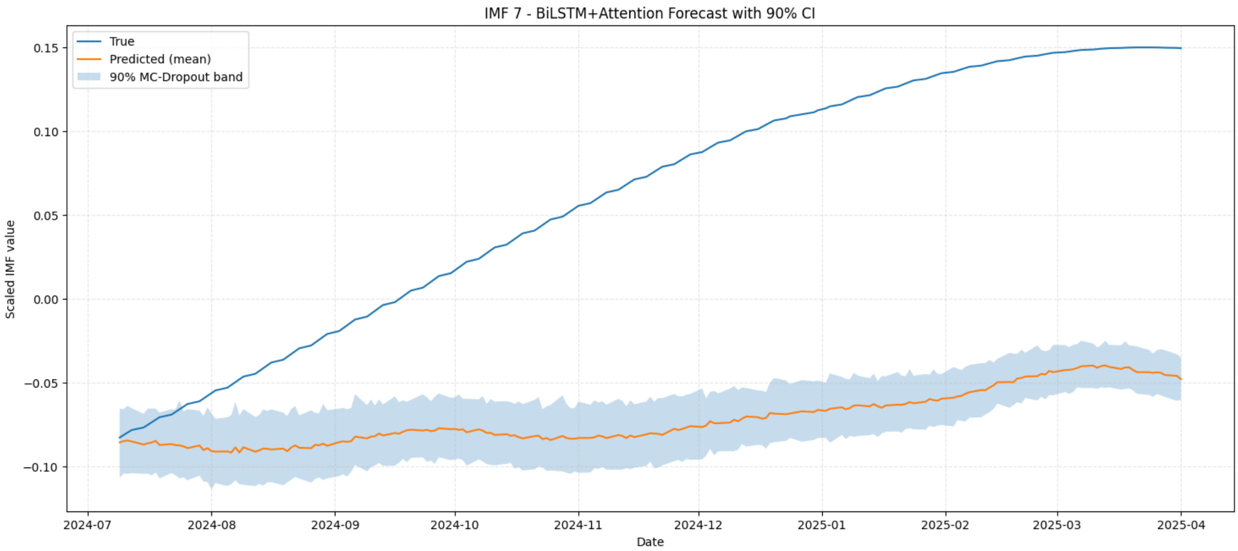

Figure 9 – Forecasting of IMF7 level

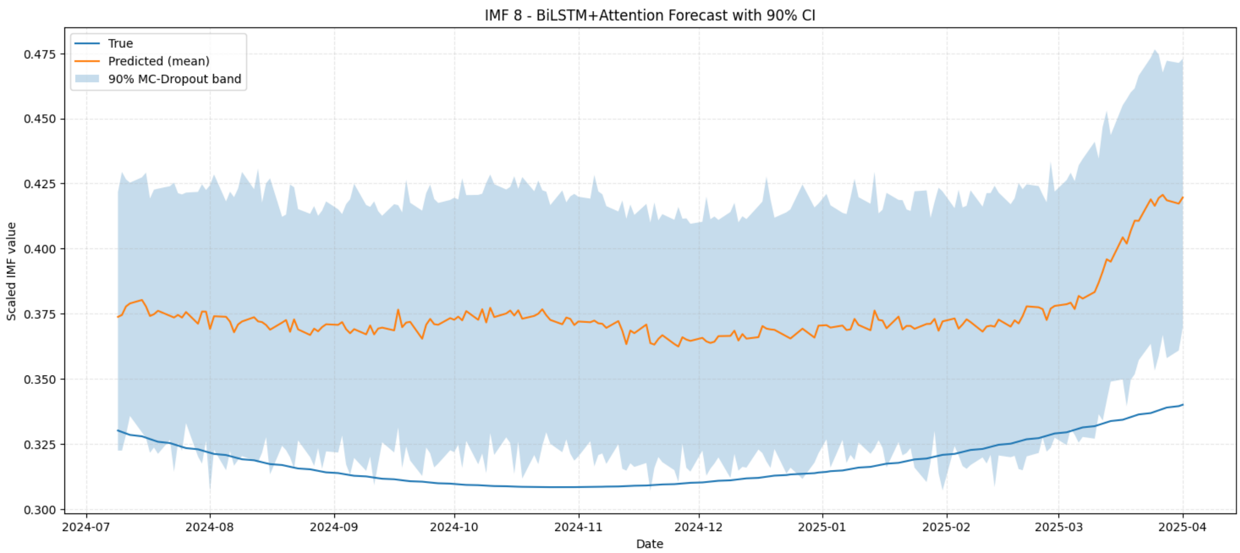

Figure 10– Forecasting of IMF78level

Figures 3 to 10 present the graphical output of BiLSTM – attention-based IMF level forecasts with 90% confidence intervals. The figures provide important insights into the model forecast performance across multiple frequency components of carbon prices. In the case of high frequency oscillations, IMF1 and IMF2 in Figures 3 and 4 show that the forecasts are smoother than compared to the actual signals which indicate that there is room for improvement in estimating rapid fluctuations. However, since they are relatively closer to the actual pattern, the model is effective in learning the general pattern of noise. The mid-level frequency is shown in IMF3 and IMF4 using Figures 5 and 6 respectively. Here, the forecasts can pick the direction and curvature of the actual signal, especially in the case of IMF4. The use of the attention model has helped to show good pattern replication by forecasts in this case. In the case of low frequency and long-term trends shown in IMF5 to IMF8 in Figures 7 to 10 respectively, the predictions are strongly aligned with the overall trajectory but it is facing difficulty in fully replicating the gradual structural shifts. Hence, in the short-term mode, the variation indicates volatile indicators which are not included in the model. These short-term fluctuation cycles might correspond to trading regimes. However, the model can predict direction and curvature accurately. Overall, this hybrid approach has been able to forecast each temporal scale of carbon pricing. Figures 11 to 18 present the training and test loss for all IMF signals. Here, in most cases, the training and test losses have become smoother except for IMF7 level which stays volatile. This means that the model is not overfitting for most of the IMF signals.

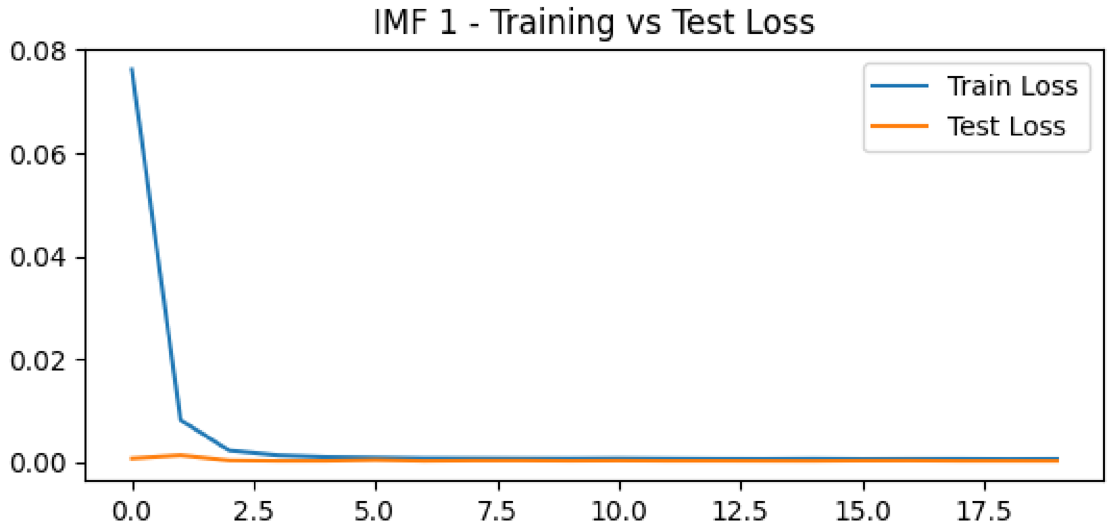

Figure 11 – Training and Test Loss for IMF1

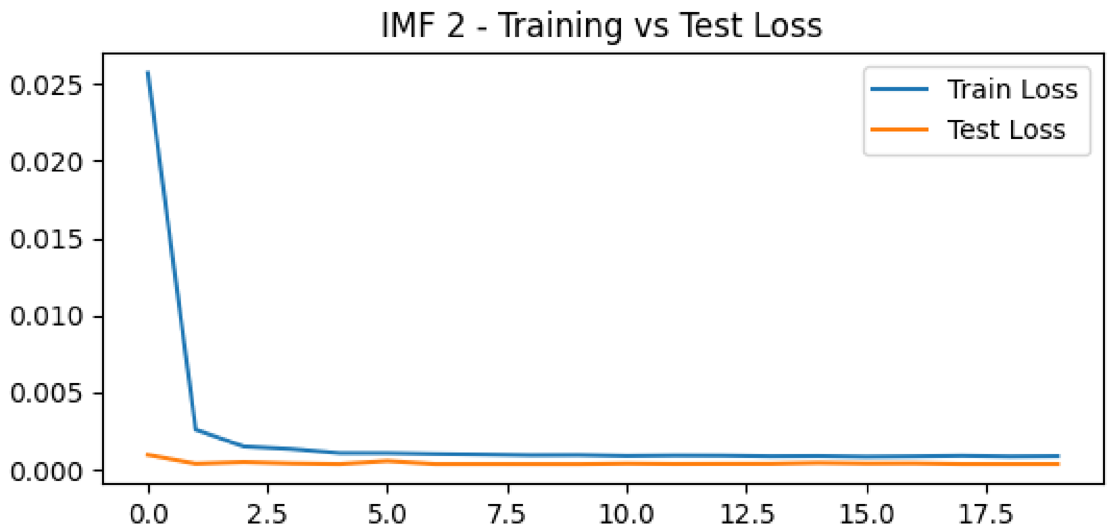

Figure 12 – Training and Test Loss for IMF2

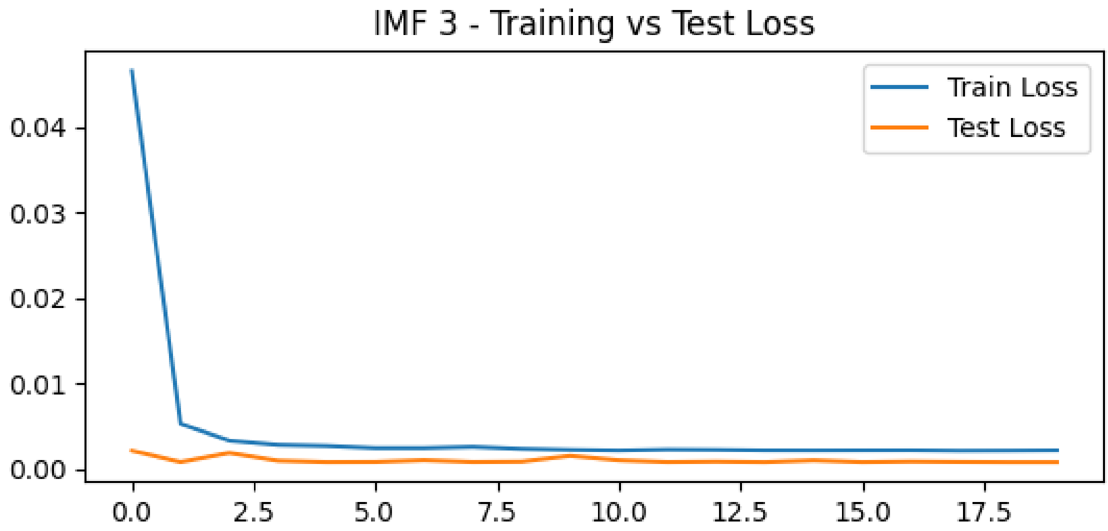

Figure 13 – Training and Test Loss for IMF3

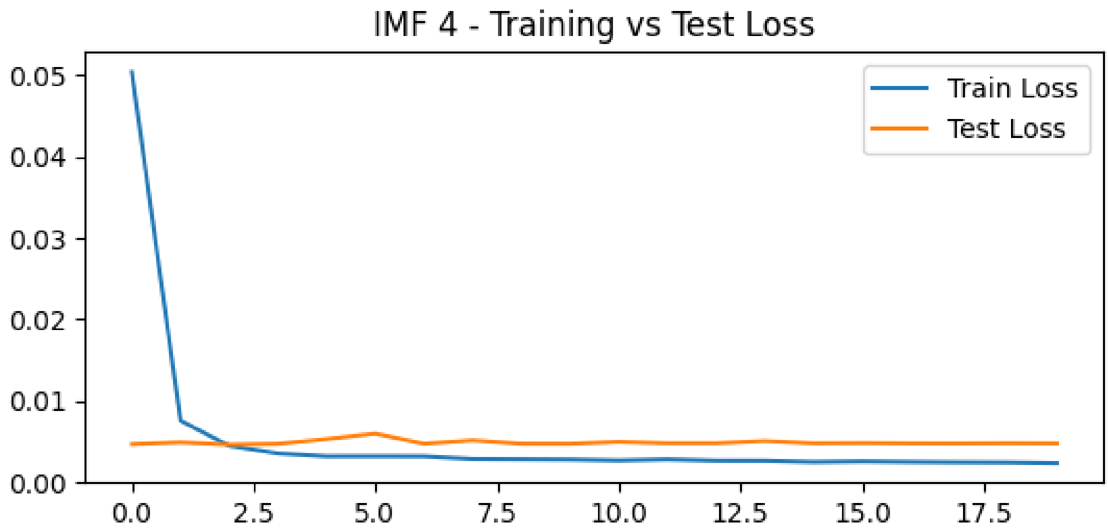

Figure 14 – Training and Test Loss for IMF4

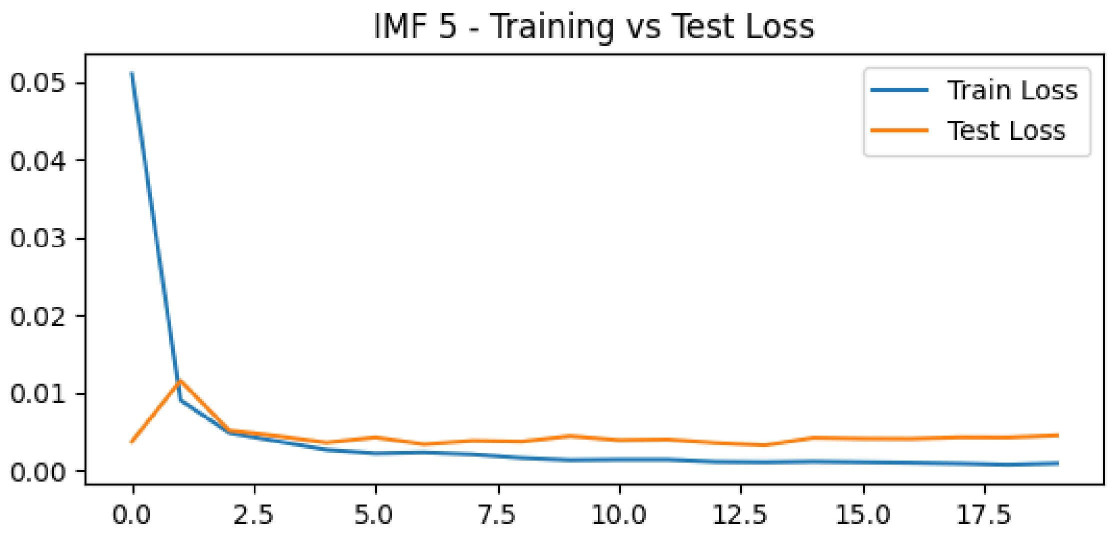

Figure 15 – Training and Test Loss for IMF5

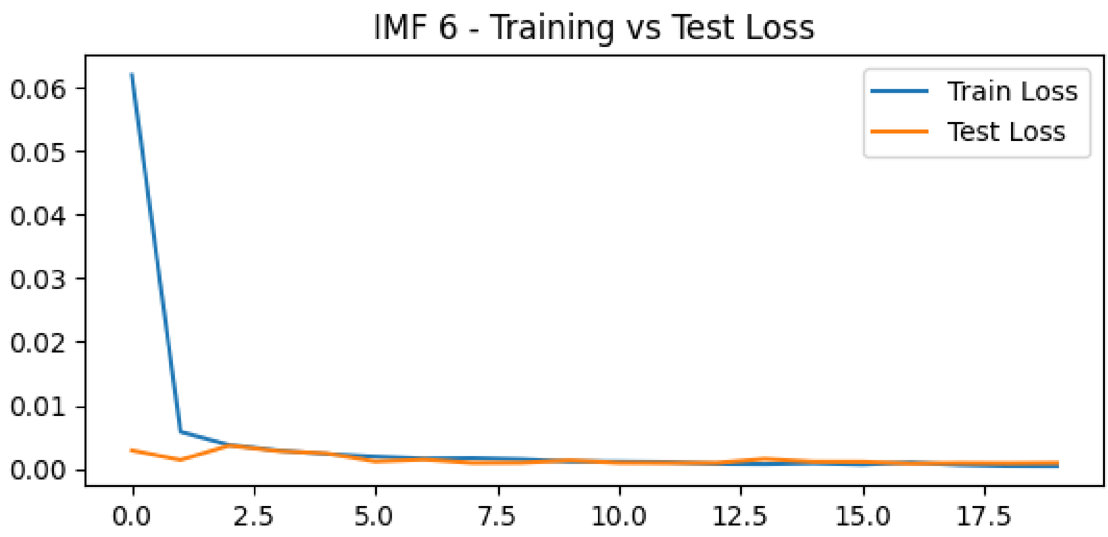

Figure 16 – Training and Test Loss for IMF6

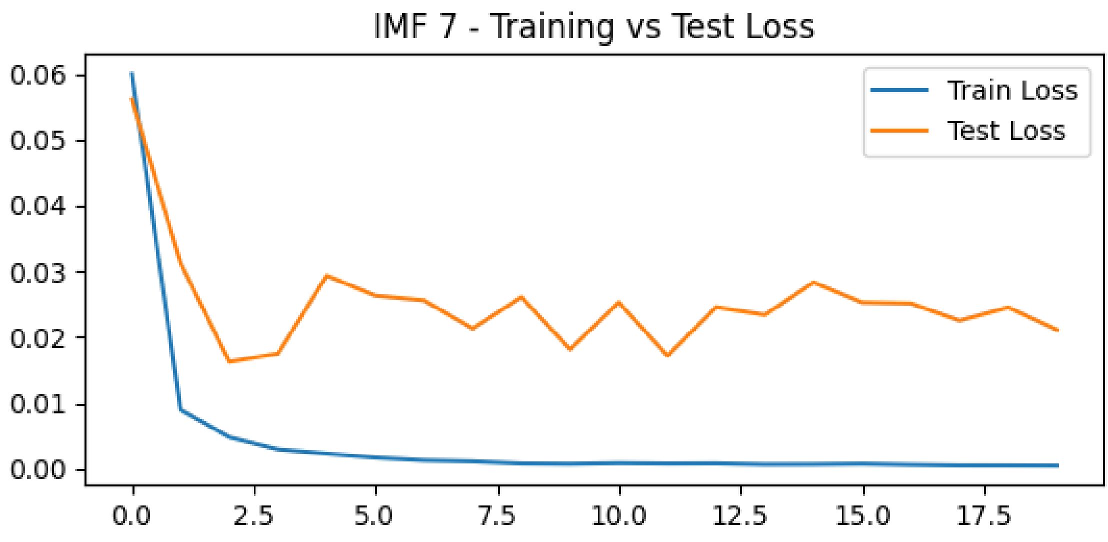

Figure 17 – Training and Test Loss for IMF7

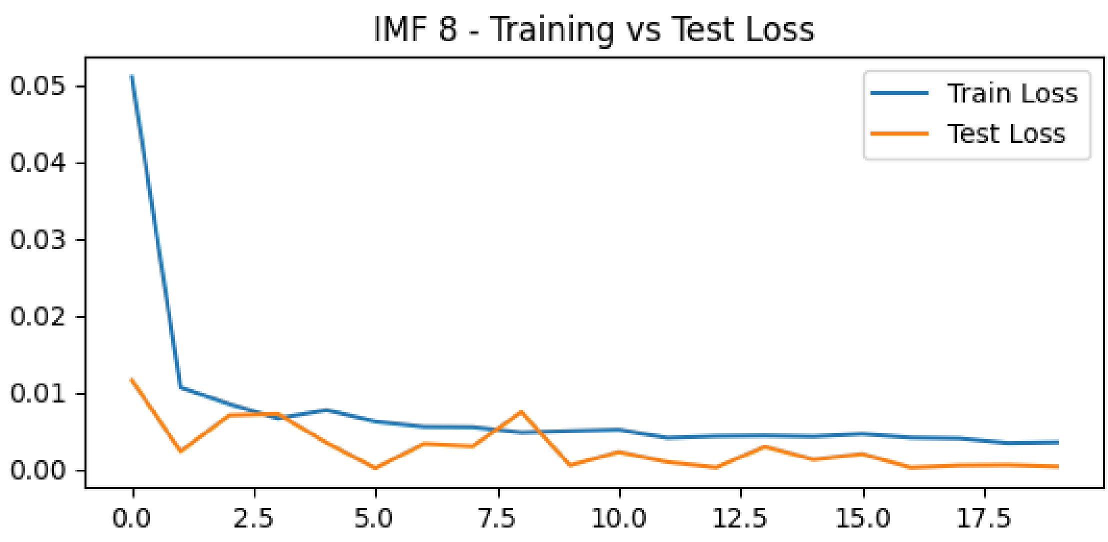

Figure 18 – Training and Test Loss for IMF8

Figures 19 to 24 provide the important features and variables in each IMF forecast using Shapley Additive Explanations (SHAP) analysis. It is used to interpret prediction determinants in the BiLSTM model (Wang, 2025). Observing the SHAP feature plots, the CBAM policy and CPI with multiple lags were key features that contributed to the current forecast of the IMFs. Correspondingly, in SHAP variables CBAM and CPI are the two most important variables contributed in forecast of IMFs. CPI as top predictor makes economic sense as it increases energy costs and carbon prices. This relation was evidenced in the EU during September 2022 where energy costs were complemented with inflation (Pous et al., 2022). CPI increases allowances per energy generator (Ampudia et al., 2022). CPI contributes to real abatement costs, changes in energy costs, altering discount rates through expectations, and shifts investment to low-carbon assets that led it to become a top predictor. Likewise, CABM reflects the market moving impact of policy announcements. Its role in prediction is because of its role in phasing out free allowances (Patterson, 2025). This policy had reduced few allowances, permanent tightening signals, alters cross-border carbon arbitrage, and shifts in demand expectations. SHAP's listing of these indicators point to regulatory anticipation literature.

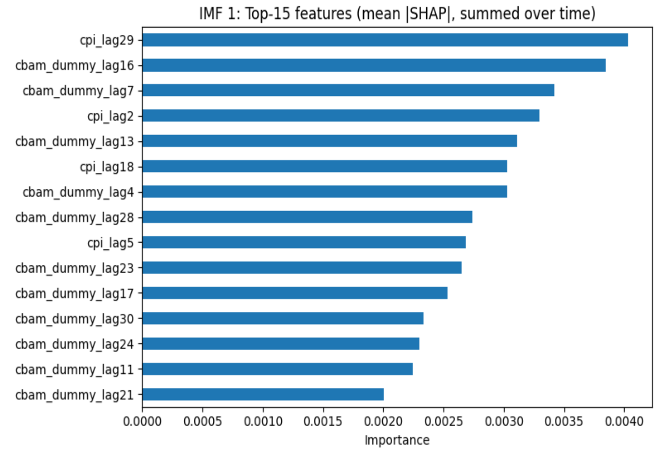

Figure 19 – Important SHAP Features IMF1

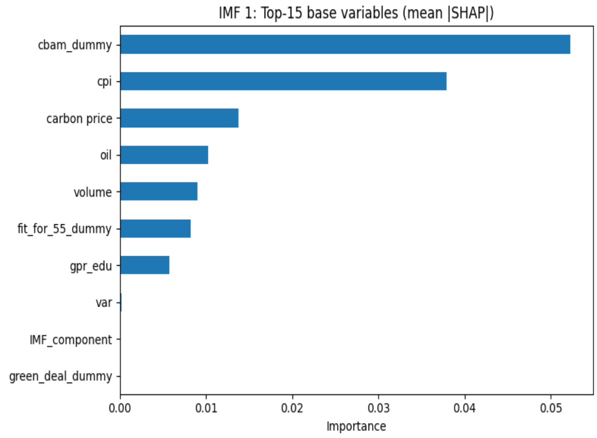

Figure 20 – Important SHAP Variables IMF1

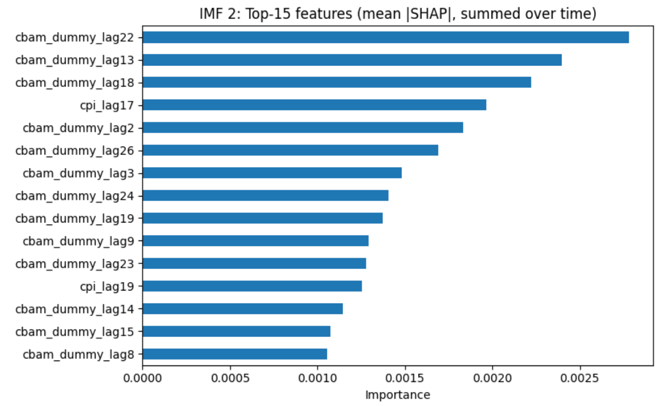

Figure 21 – Important SHAP Features IMF2

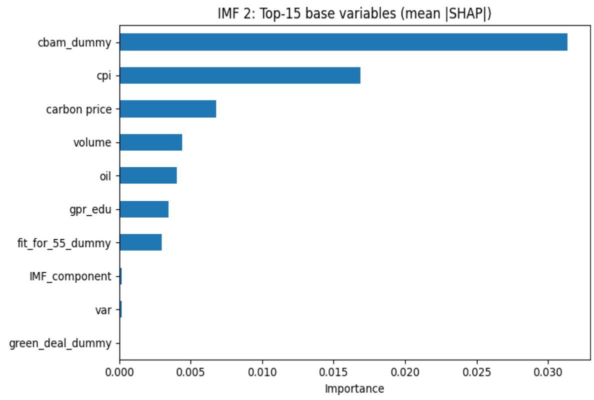

Figure 22 – Important SHAP Variables IMF2

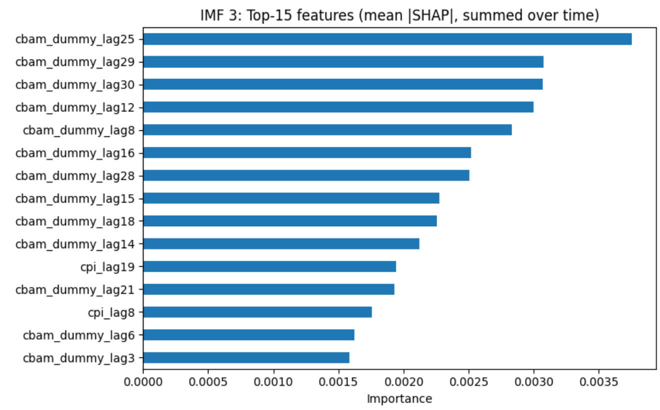

Figure 23 – Important SHAP Features IMF3

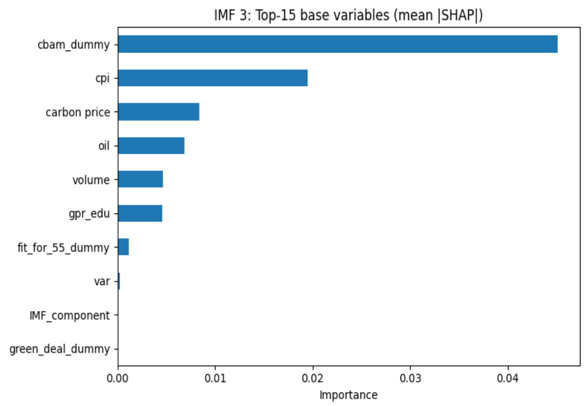

Figure 24 – Important SHAP Variables IMF3

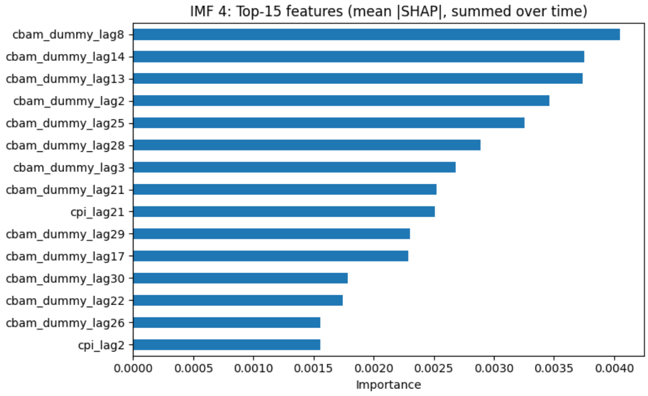

Figure 25 – Important SHAP Features IMF4

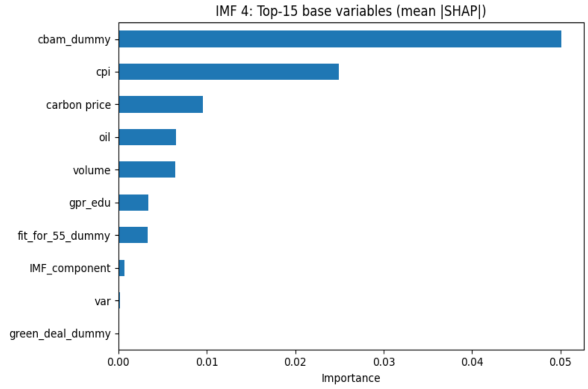

Figure 26 – Important SHAP Variables IMF4

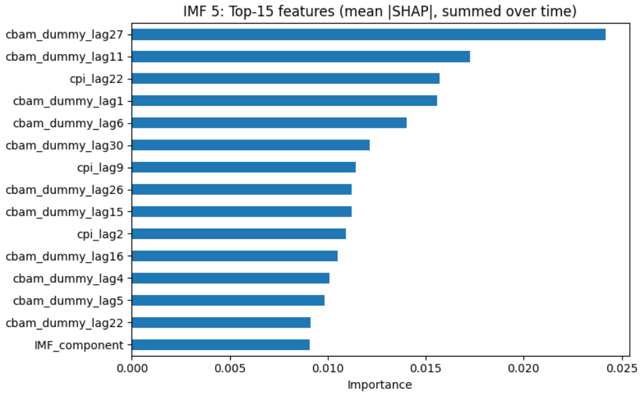

Figure 27 – Important SHAP Features IMF5

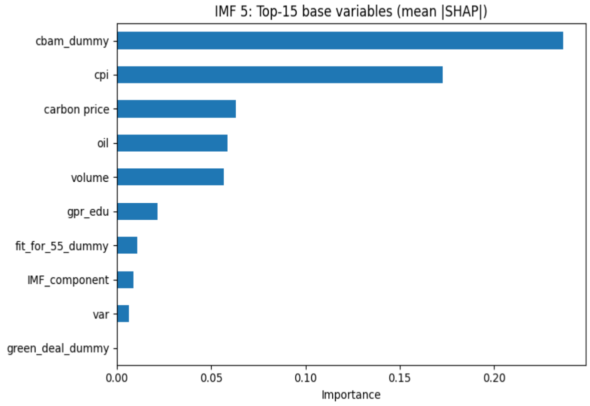

Figure 28 – Important SHAP Variables IMF5

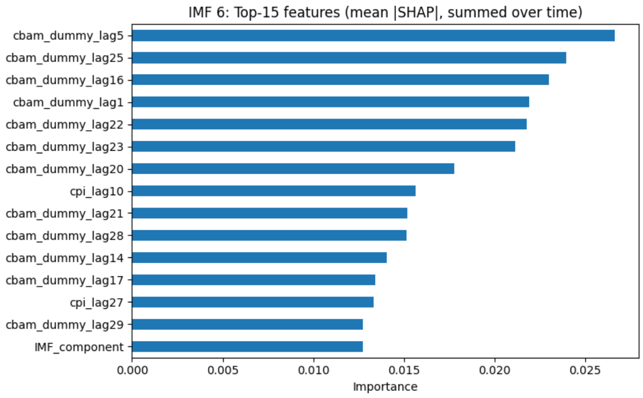

Figure 29 – Important SHAP Features IMF6

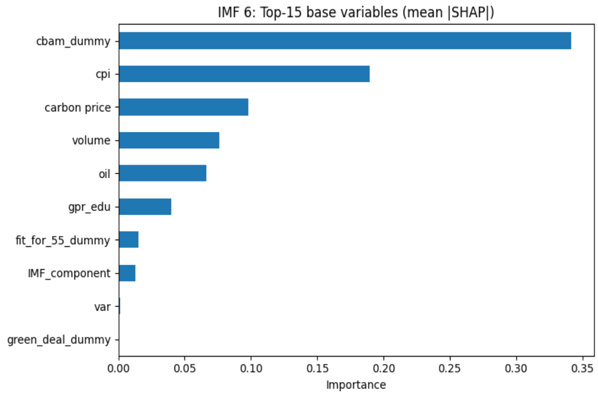

Figure 30 – Important SHAP Variables IMF6

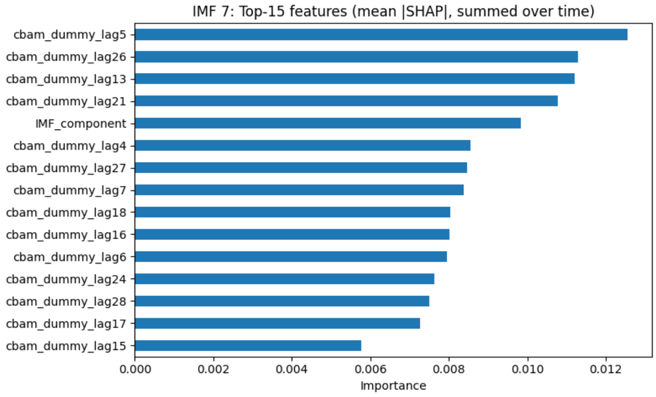

Figure 31 – Important SHAP Features IMF7

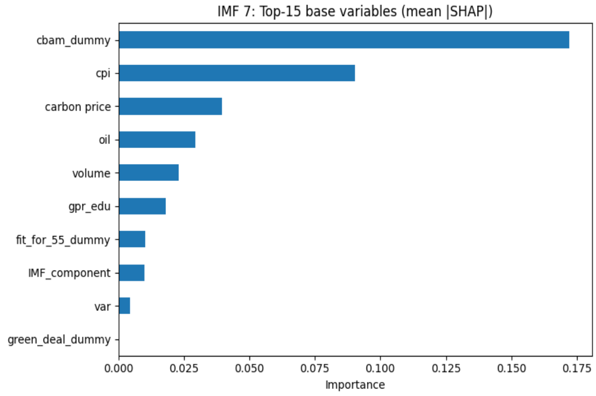

Figure 32 – Important SHAP Variables IMF7

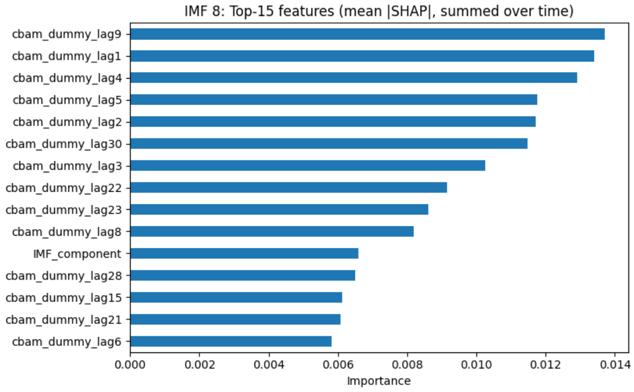

Figure 33 – Important SHAP Features IMF8

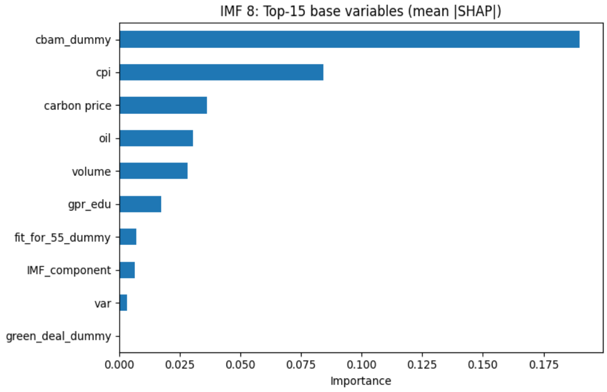

Figure 34 – Important SHAP Variables IMF8

4.2. Final Reconstructed Signal Forecast

Following the IMF level forecasts, the signals are aggregated to reconstruct the overall carbon price signal. The actual signal is shown in Figure 35. The RMSE of the overall model is 4.59. This estimated RMSE value is significantly better than simple LSTM models tested by the study that did not include the exogenous factors. This RMSE is higher than the individual model RMSEs because when adding together the noise is also added. The high RMSE value is due to error propagation across components. Each IMF includes its own deviations which accumulates when reconstructed to the original. This high RMSE shows accumulated uncertainty rather than a deterioration of model performance.

The outcome in Figure 10 shows that the hybrid EMD-BiLSTM-attention model can learn the multi-resolution signal of the data. The 95% confidence interval shows that most of the actual data falls within the interval. This shows that the model successfully calibrates the uncertainty estimates. The temporary deviation of the actual data outside the confidence interval between 2025-01 to 2025-03 are expected because of an unusually cold winter in 2024/2025 and increased disruptions of Russian gas supply and Middle Eastern oil supply.

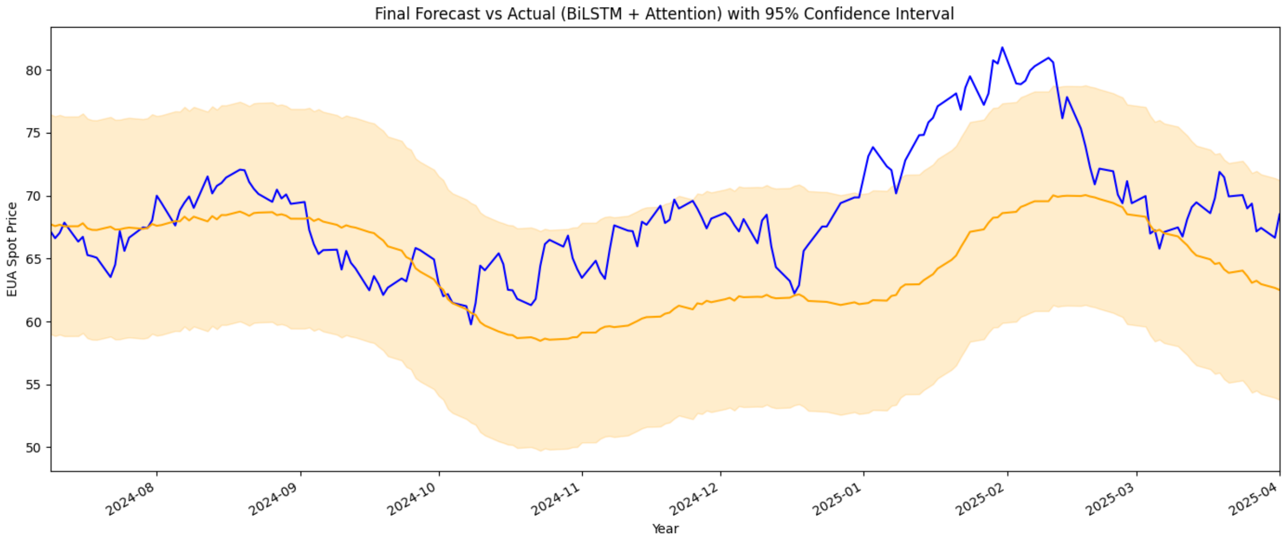

Figure 35 – Reconstructed Signal Forecast

4.3. Discussions

The outcomes highlight the importance of integrating advanced signal decomposition techniques with deep learning models for carbon price forecasting by controlling lags, volatility, macroeconomic, and policy environments. The iteration process of the study started using no exogenous variables that had RMSE more than 10 but this study included climate policies using dummies and other macroeconomic variables which had improved the RMSE. The attention mechanism helped the learning of the BiLSTM model in the case of high frequency signals. The final RMSE of 4.59 showed that the model had shown significant improvement. The advantage of the model is that it was able to learn through multiple time-scale behaviors estimated using EMD. This model is not a mere artifact, rather it reflects the contribution of economic structure of carbon markets. The study was able to support hypothesis H1 in IMF1 – IMF4, hypothesis H2 in IMF3 – IMF6 and hypothesis H3 in IMF6 – IMF8.

The study incorporated multiple explanatory variables that enhanced its robustness and interpretability. The results of the study are supporting the outcome of studies like Chevallier (2011a), Fragkos and Fragkiadakis (2022), and Mengistu et al. (2019) which have used the macroeconomic variables in explaining the carbon pricing. It also supports the outcome policy event effects by past studies (Almondo, 2025; Böning et al., 2023; Weishaar, 2023). The SHAP analysis highlighted the contributory role of CBAM and CPI in forecasting which were prominent compared to other indicators. The individual IMF forecasts showed variation in the performance levels across different frequencies. The model for carbon markets constituted of multiple temporal layers in which short term fluctuations are driven by trading activity and liquidity conditions, medium term is influenced by fuel-switching incentives, and long term is shaped by regulatory tightening and policy.

The models show better performance at high frequency or lower order showed by IMF1 – IMF3. This captures short run volatility, speculative adjustments, and rapid responses. The use of the BiLSTM model with self-attention helped in modeling these localized nonlinear dynamics. This means that the short-term EUA has learnable behavior rather than random behavior. In contrast to the lower frequencies/higher order, the IMF model showed a higher RMSE which is likely due to complexities in long-term structural trends. Since they are inherently political and expectation driven, it is harder to model using empirical data patterns. The behaviors are forward looking in long term trends and a higher RMSE denotes structural complexity rather than model weakness. This heterogeneity in factors supports hypothesis H5.

However, as shown in Figure 19, despite minor lags and peak tracking the reconstruction forecasts are having RMSE of 4.59. The results provide evidence for the effectiveness of a hybrid deep learning model in the case of carbon market behavior. This model reflects the bias-variance trade off linked to decomposition and reconstruction. While the decomposed models reduce noise and show better local learning performance, their reconstruction accumulates component level uncertainty too. The study summarizes that the proposed model delivers a balance of interpretability and predictive strength and can be used for academic policy and financial forecasting of carbon markets.

Compared to Naïve, moving average and simple exponential smoothing, the proposed model had superior performance (supporting hypothesis H4). The traditional benchmarks assumed linear persistence or linear smoothing which was inadequate in this data case and was driven by nonlinear regimes and policy driven breaks. The lower RMSE advocated that the deep learning architectures are guided by economic fundamentals and signal decomposition. It is to be noted that the better RMSE is not only attributed to architectural complexity but rather it is based on appropriate macroeconomic and policy variables.

Overall, it is seen that carbon prices have layered interaction. The forecasting performance showed improvement when the multi-horizon structure is modeled.

5. Conclusions and Implications

This study ventures into the carbon market dynamics and climate finance and proposes a hybrid carbon price forecasting model. The model used combines the Empirical Model Decomposition (EMD), Bidirectional Long Short-Term Memory (BiLSTM), and attention mechanism to predict the carbon market named EU ETS Phase 4 spot prices. The selection of this European market is merited by the liquidity and maturity of this market. The model uses intrinsic structural features extracted from carbon price signals using EMD and external fundamentals using oil prices, trading volume, inflation, geopolitical risk, and major climate policy events like Green Deal, CBAM, and Fit-for-55 using dummy variables.

The empirical model starts with no exogenous variable using an LSTM model and then builds towards the best model based on a selection of appropriate macroeconomic fundaments. The result demonstrates that the forecast can achieve RMSE of 4.59 at a reconstructed signal level while the model performs significantly well across decomposed IMF levels. The model can replicate the trajectory and curvature in low frequency and show low forecast error in high frequency cases. Thus, the model performs better in lower frequency (and long-term fluctuations). While the high frequency is dominated by noise rather than cycles, in the EU ETS market the price movements that are dependent on exogenous shocks, speculative behavior, and microstructural noise may not provide learnable patterns using macroeconomic data.

This study compiles several policy implications. Theoretically the estimates showed that the carbon price changes across multiple time horizons are determined by energy transmission, expectations, and credibility. The findings highlight that if the markets are integrated like this European market, the exogenous drivers improve the data driven forecasting performance. In depth exploration of literature can help find suitable fundaments that can provide a more realistic prediction of carbon price dynamics. This study also used the policy intervention dummies to incorporate the structural change arising from regulatory interventions. The model proposed that such changes must be used in models to explain sudden changes in the patterns. Theoretically, the hybrid model with SHAP helped to make the model interpretable under the principles of explainable Artificial Intelligence (AI).

Policy makers must reinforce the importance of a transparent, forward-guiding policy that can lead to market actors responding according to expectations and shaping carbon prices according to fundamentals. Key features like CBAM regime and CPI are to be observed and managed to regulate carbon pricing. This algorithm can help investors and regulated firms to anticipate price movements enabling robust compliance planning, investment decisions, and hedging strategies that are designed for zero emissions. Since this model is based on exogenous factors, it can also predict the market pressure on the carbon prices based on the expected or actual incidence of independent variables. This can help businesses to anticipate the direction of future carbon prices.

Thus, this study contributes both methodologically and practically to the domain of carbon market forecasting. The results show the superiority of hybrid AI models integrated with structural and policy changes in the market. This model can be deployed for high performance forecasting. This study has advanced literature by innovating an EMD-LSTM framework that performs join decomposition of inputs and inclusion of structural policy shifts.

There are some limitations of the model deployed by this study. In a smaller training data set, LSTM may overfit. The results are limited to the used macroeconomic data that can help in forecasting lower frequencies but, for higher frequencies, more frequent data is required. Since such data can vary region to region it might not be possible acquire such data at macroeconomic level. Future studies can venture into mixed frequency modelling using surprise transformation or Mixed Data Sampling (MIDAS) models to further improve the forecasting ability of these models. This hybrid model is purely data driven so any unprecedented regulatory shifts may lead to forecast instability. Future studies can incorporate unknown breakpoint detection and regime-switching mechanisms to improve performance.

References

Almondo, R. (2025). *A data-driven analysis of Green Energy companies in Europe: Market dynamics, financing sources, and key profitability drivers* [Laurea, Politecnico di Torino]. https://webthesis.biblio.polito.it/35581/

Ampudia, M., Bua, G., Kapp, D., & Salakhova, D. (2022). The role of speculation during the recent increase in EU emissions allowance prices. *ECB Economic Bulletin*, *3*. https://www.ecb.europa.eu/press/economic-bulletin/focus/2022/html/ecb.ebbox202203_06~ca1e9ea13e.en.html

Bayer, P., & Aklin, M. (2020). The European Union Emissions Trading System reduced CO2 emissions despite low prices. *Proceedings of the National Academy of Sciences*, *117*(16), 8804–8812. https://doi.org/10.1073/pnas.1918128117

Benz, E., & Trück, S. (2009). Modeling the price dynamics of CO2 emission allowances. *Energy Economics*, *31*(1), 4–15. https://doi.org/10.1016/j.eneco.2008.07.003

Böning, J., Di Nino, V., & Folger, T. (2023). *Benefits and Costs of the ETS in the EU, a Lesson Learned for the CBAM Design* (SSRN Scholarly Paper No. 4335984). Social Science Research Network. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4335984

Bunn, D., & Fezzi, C. (2007). Interaction of European Carbon Trading and Energy Prices. *Fondazione Eni Enrico Mattei Working Papers*. https://services.bepress.com/feem/paper123

Byun, S. J., & Cho, H. (2013). Forecasting carbon futures volatility using GARCH models with energy volatilities. *Energy Economics*, *40*, 207–221. https://doi.org/10.1016/j.eneco.2013.06.017

Cai, Y., Guo, J., & Tang, Z. (2022). An EEMD-CNN-BiLSTM-attention neural network for mixed frequency stock return forecasting. *Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology*, *43*(1). https://journals.sagepub.com/doi/abs/10.3233/JIFS-213276

Caldara, D., & Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, *112*(4), 1194–1125.

Chevallier, J. (2011a). A model of carbon price interactions with macroeconomic and energy dynamics. *Energy Economics*, *33*(6), 1295–1312. https://doi.org/10.1016/j.eneco.2011.07.012

Chevallier, J. (2011b). Nonparametric modeling of carbon prices. *Energy Economics*, *33*(6), 1267–1282. https://doi.org/10.1016/j.eneco.2011.03.003

Chevallier, J. (2011c). Price Relationships in the EU Emissions Trading System. In *Green Finance and Sustainability: Environmentally-Aware Business Models and Technologies*. IGI Global. https://www.igi-global.com/chapter/green-finance-sustainability/www.igi-global.com/chapter/green-finance-sustainability/53252

Colominas, M. A., Schlotthauer, G., & Torres, M. E. (2014). Improved complete ensemble EMD: A suitable tool for biomedical signal processing. *Biomedical Signal Processing and Control*, *14*, 19–29. https://doi.org/10.1016/j.bspc.2014.06.009

Creti, A., Jouvet, P.-A., & Mignon, V. (2012). Carbon price drivers: Phase I versus Phase II equilibrium? *Energy Economics*, *34*(1), 327–334. https://doi.org/10.1016/j.eneco.2011.11.001

Delarue, E., Voorspools, K., & D'haeseleer, W. (2008). Fuel Switching in the Electricity Sector under the EU ETS: Review and Prospective. *Journal of Energy Engineering*, *134*(2), 40–46. https://doi.org/10.1061/(ASCE)0733-9402(2008)134:2(40)

Dragomiretskiy, K., & Zosso, D. (2014). Variational Mode Decomposition. *IEEE Transactions on Signal Processing*, *62*(3), 531–544. https://doi.org/10.1109/TSP.2013.2288675

Duan, K., Ren, X., Shi, Y., Mishra, T., & Yan, C. (2021). The marginal impacts of energy prices on carbon price variations: Evidence from a quantile-on-quantile approach. *Energy Economics*, *95*, 105131. https://doi.org/10.1016/j.eneco.2021.105131

Duan, K., Wang, R., Chen, S., & Ge, L. (2023). Exploring the predictability of attention mechanism with LSTM: Evidence from EU carbon futures prices. *Research in International Business and Finance*, *66*, 102020. https://doi.org/10.1016/j.ribaf.2023.102020

Ellerman, A. D., Convery, F. J., & Perthuis, C. de. (2010). *Pricing Carbon: The European Union Emissions Trading Scheme*. Cambridge University Press.

Establishing a Carbon Border Adjustment Mechanism, No. Document 52021PC0564 (2021). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021PC0564

Fan, X., Li, S., & Tian, L. (2015). Chaotic characteristic identification for carbon price and an multi-layer perceptron network prediction model. *Expert Systems with Applications*, *42*(8), 3945–3952. https://doi.org/10.1016/j.eswa.2014.12.047

Fell, H., & Morgenstern, R. D. (2010). Alternative Approaches to Cost Containment in a Cap-and-Trade System. *Environmental and Resource Economics*, *47*, 175–197.

Feng, Z.-H., Zou, L.-L., & Wei, Y.-M. (2011). Carbon price volatility: Evidence from EU ETS. *Applied Energy*, *88*(3), 590–598. https://doi.org/10.1016/j.apenergy.2010.06.017

'Fit for 55': Delivering the EU's 2030 Climate Target on the Way to Climate Neutrality, No. 52021DC0550 (2021). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021DC0550

Fragkos, P., & Fragkiadakis, K. (2022). Analyzing the Macro-Economic and Employment Implications of Ambitious Mitigation Pathways and Carbon Pricing. *Frontiers in Climate*, *4*. https://doi.org/10.3389/fclim.2022.785136

Guidolin, M. (2011). Markov Switching Models in Empirical Finance. In D. M. Drukker (Ed.), *Missing Data Methods: Time-Series Methods and Applications* (world). Emerald Group Publishing Limited. https://doi.org/10.1108/S0731-9053(2011)000027B004

Hua, J., Wang, R., Hu, Y., Chen, Z., Chen, L., Osman, A. I., Farghali, M., Huang, L., Feng, J., Wang, J., Zhang, X., Zhou, X., & Yap, P.-S. (2025). Artificial intelligence for calculating and predicting building carbon emissions: A review. *Environmental Chemistry Letters*, *23*(3), Article 3. https://doi.org/10.1007/s10311-024-01799-z

Huang, Y., Dai, X., Wang, Q., & Zhou, D. (2021). A hybrid model for carbon price forecasting using GARCH and long short-term memory network. *Applied Energy*, *285*, 116485. https://doi.org/10.1016/j.apenergy.2021.116485

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, *71*, 101526. https://doi.org/10.1016/j.irfa.2020.101526

Jiang, W., Zhang, Y., & Wang, K.-H. (2024). Analyzing the connectedness among geopolitical risk, traditional energy and carbon markets. *Energy*, *298*, 131411. https://doi.org/10.1016/j.energy.2024.131411

Lau, C. K., Soliman, A. M., Albasu, J., & Gozgor, G. (2023). Dependence structures among geopolitical risks, energy prices, and carbon emissions prices. *Resources Policy*, *83*, 103603. https://doi.org/10.1016/j.resourpol.2023.103603

Lindner, J. (2025). *Rmse Statistics Statistics: Market Data Report 2025*. World Metrics Org. https://worldmetrics.org/rmse-statistics/

Luo, X., Yu, R., Guo, Y., Jia, H., & Liu, D. (2022). Carbon Price Prediction of LSTM Method Based on Attention Mechanism. *2022 4th International Conference on Smart Power & Internet Energy Systems (SPIES)*, 2198–2202. https://doi.org/10.1109/SPIES55999.2022.10082179

Martin, R., Muûls, M., de Preux, L. B., & Wagner, U. J. (2014). Industry Compensation under Relocation Risk: A Firm-Level Analysis of the EU Emissions Trading Scheme. *American Economic Review*, *104*(8), 2482–2508.

Mengistu, A. T., Benitez, P., Tamru, S., Medhin, H., & Toman, M. (2019). Exploring Carbon Pricing in Developing Countries: A Macroeconomic Analysis in Ethiopia. *Sustainability*, *11*(16), Article 16. https://doi.org/10.3390/su11164395

Naeem, M., Aamir, M., Yu, J., & Albalawi, O. (2024). A Novel Approach for Reconstruction of IMFs of Decomposition and Ensemble Model for Forecasting of Crude Oil Prices. *IEEE Access*, *12*, 34192–34207. https://doi.org/10.1109/ACCESS.2024.3370440

Nava Morales, N. C. (2016). Analysis of high-frequency financial data over different timescales: A Hilbert-Huang transform approach [Doctoral, UCL (University College London)]. In *Doctoral thesis, UCL (University College London).* UCL. https://discovery.ucl.ac.uk/id/eprint/1530091/

Newell, R. G., Pizer, W. A., & Raimi, D. (2014). Carbon Market Lessons and Global Policy Outlook. *Science*, *343*(6177), 1316–1317. https://doi.org/10.1126/science.1246907

Patterson, W. (2025). *Falling allowance supply to tighten EU carbon market*. ING Think. https://think.ing.com/articles/falling-allowance-supply-to-tighten-eu-carbon-market/

Pous, P. D., Patuleia, A., Brown, S., & Rosslowe, C. (2022). More renewables, less inflation—Restoring EU economic stability through investment in renewables. *E3G Briefing Paper*. https://www.e3g.org/wp-content/uploads/E3G-EMBER-Briefing-More-renewables-less-inflation.pdf#:~:text=high,Figure%201

Ren, R., Li, J., Li, Y., Huang, S., Shen, J., Li, W., Le, J., & Wang, S. (2025). *A Hybrid Deep Learning based Carbon Price Forecasting Framework with Structural Breakpoints Detection and Signal Denoising* (No. arXiv:2511.04988). arXiv. https://doi.org/10.48550/arXiv.2511.04988

Soliman, A. M., & Nasir, M. A. (2019). Association between the energy and emission prices: An analysis of EU emission trading system. *Resources Policy*, *61*, 369–374. https://doi.org/10.1016/j.resourpol.2018.12.005

The European Green Deal, No. Document 52019DC0640 (2019). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2019:640:FIN

van Jaarsveldt, C., Peters, G. W., Ames, M., & Chantler, M. (2023). Tutorial on Empirical Mode Decomposition: Basis Decomposition and Frequency Adaptive Graduation in Non-Stationary Time Series. *IEEE Access*, *11*, 94442–94478. https://doi.org/10.1109/ACCESS.2023.3307628

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł. ukasz, & Polosukhin, I. (2017). Attention is All you Need. *Advances in Neural Information Processing*

Systems, *30*. https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html

Verde, S. F., & Borghesi, S. (2022). The International Dimension of the EU Emissions Trading System: Bringing the Pieces Together. *Environmental and Resource Economics*, *83*(1), Article 1. https://doi.org/10.1007/s10640-022-00705-x

Wang, H., Tan, Z., Zhang, A., Pu, L., Zhang, J., & Zhang, Z. (2023). Carbon market price prediction based on sequence decomposition-reconstruction-dimensionality reduction and improved deep learning model. *Journal of Cleaner Production*, *425*, 139063. https://doi.org/10.1016/j.jclepro.2023.139063

Wang, Y., Qin, L., Wang, Q., Chen, Y., Yang, Q., Xing, L., & Ba, S. (2023). A novel deep learning carbon price short-term prediction model with dual-stage attention mechanism. *Applied Energy*, *347*, 121380. https://doi.org/10.1016/j.apenergy.2023.121380

Wang, Z. (2025). *Interpretable Deep Learning for Heat Demand Forecasting in Buildings: Explaining BiLSTM Predictions with SHAP*. https://urn.kb.se/resolve?urn=urn:nbn:se:ltu:diva-113814

Weishaar, S. E. (2023). Chapter 8: Green deal transition and cooperation. In S. E. Weishaar, E. Kim, & F. Tiche (Eds), *Climate and Energy Law and Policy in the EU and East Asia* (pp. 154–180). Elgar Online. https://www.elgaronline.com/edcollchap/book/9781035301157/book-part-9781035301157-16.xml

World Bank. (2023). *State and Trends of Carbon Pricing 2023*. World Bank Group. https://www.worldbank.org/en/news/press-release/2023/05/23/record-high-revenues-from-global-carbon-pricing-near-100-billion

Yu, L., Li, C., Wang, J., & Sun, H. (2024). A hybrid model for predicting the carbon price in Beijing: A pilot low-carbon city in China. *Frontiers in Physics*, *12*. https://doi.org/10.3389/fphy.2024.1427794

Zhan, X., & Li, Y. (2025). Price Volatility and Risk Measurement of EU Carbon Futures under Structural Mutation. *Academic Journal of Business & Management*, *7*(6), 15–22. https://doi.org/10.25236/AJBM.2025.070603

Zhang, K., Yang, X., Wang, T., Thé, J., Tan, Z., & Yu, H. (2023). Multi-step carbon price forecasting using a hybrid model based on multivariate decomposition strategy and deep learning algorithms. *Journal of Cleaner Production*, *405*, 136959. https://doi.org/10.1016/j.jclepro.2023.136959

Zhang, N., Lin, A., & Shang, P. (2017). Multidimensional k-nearest neighbor model based on EEMD for financial time series forecasting. *Physica A: Statistical Mechanics and Its Applications*, *477*, 161–173. https://doi.org/10.1016/j.physa.2017.02.072

Zhang, W., & Wu, Z. (2022). Optimal hybrid framework for carbon price forecasting using time series analysis and least squares support vector machine. *Journal of Forecasting*, *41*(3), 615–632. https://doi.org/10.1002/for.2831

Zhu, B., Han, D., Wang, P., Wu, Z., Zhang, T., & Wei, Y.-M. (2017). Forecasting carbon price using empirical mode decomposition and evolutionary least squares support vector regression. *Applied Energy*, *191*, 521–530. https://doi.org/10.1016/j.apenergy.2017.01.076

Zhu, B., & Wei, Y. (2013). Carbon price forecasting with a novel hybrid ARIMA and least squares support vector machines methodology. *Omega*, *41*(3), 517–524. https://doi.org/10.1016/j.omega.2012.06.005

Zhu, B., Ye, S., Wang, P., Chevallier, J., & Wei, Y. M. (2021). Forecasting carbon price using a multi-objective least squares support vector machine with mixture kernels. *Journal of Forecasting*, *41*(1), 100–117.

Zhu, B., Zhang, J., Wan, C., Chevallier, J., & Wang, P. (2023). An evolutionary cost-sensitive support vector machine for carbon price trend forecasting. *Journal of Forecasting*, *42*(4), 741–755. https://doi.org/10.1002/for.2916

Zhu, J., Wu, P., Chen, H., Liu, J., & Ligang, Z. (2018). Carbon price forecasting with variational mode decomposition and optimal combined model. *Physica A: Statistical Mechanics and Its Applications*, *519*. https://doi.org/10.1016/j.physa.2018.12.017