Towards Transparent Carbon Trading - Integrating Explainable AI and GANs for Circular Economy Driven Price Prediction

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Abstract **— Emissions Trade Systems (ETS) and Circular Economy (CE) are currently the biggest ways of engaging in emissions management. However, traditional emission trade mechanisms face roadblocks in terms of computation speed and forecasting accuracy. Whilst AI-centric solutions have solved this to an extent, they are found to be engulfed with problems like issues in validating carbon credits, being unable to consider external driving factors for carbon prices and lack of interpretation of the price-related insights generated. To overcome this study proposes a hybrid novel carbon price forecasting model comprising of hybrid Deep Convolutional Generative Adversarial Network (DCGAN) coupled with Explainable AI (XAI) for interpretable price forecasting. The study serves as a testament for integration of DCGAN and XAI based models as its findings uncover key insights related to carbon prices which can help stakeholders to improve their emissions trade performance significantly in real time and improve circular economy (CE) based lifecycle development.**

Keywords— DCGAN, XAI, N-Beats, Random Forest, Price Forecasting, Emission Trade Systems

I. Introduction

In recent years, the need of devising robust methods for tackling excessive CO2 emissions has grown. Whilst several initiatives have been taken, there is very little impact of these within the corporate landscape [1]. This necessitates the demand for solutions that actively encourages business to reduce carbon emissions [2]. So far there are 2 solutions that have emerged to do exactly what is intended - ETS and CE. On one hand ETS encourages carbon offsetting through exchange of carbon credit units (CCUs) [3]. On the other hand, CE achieves the same through development of closed loop systems for waste minimization [4]. Owing to the similar nature of intent both methods employ i.e. - reducing excessive wastage albeit in different forms, an opportunity to assimilate them is realized from a theoretical perspective, as they both exhibit benefits like supply chain optimization, better emission management and easy policy alignment [5], [6]. However, on the practical front, a number of implementation gaps emerge that prohibit the same. Past studies indicate that traditional forecasting methods fail in terms of assessing complex parameters within carbon price, something which is necessary due to its interdisciplinary nature [7]. Whilst AI has been able to effectively mitigate this, it has introduced a newer set of problems. Current AI based forecasting methods fail to authenticate the CCUs generated in terms of applicability, are unable to consider external factors in the global context like energy prices and are not able to provide insights that can be easily interpreted by stakeholders [8], [9], [10]. On the CE front, AI tends to grapple with similar issues as it prioritizes individualistic goals over large scale interests, ignoring organizational goals and potentially steering away from emission reduction goals from a compliance perspective [11], [12]. Such gaps pave the need for innovative solutions to be devised which can mitigate them effectively. Sensing the need to do the same, this study proposes a hybrid interpretable framework for resilient carbon price prediction, by harnessing the power of XAI and DCGAN for generating day-ahead carbon prices and interpretable insights into what influences the predicted carbon prices in real time.

II. Methodology Adopted

A. *Techniques Implemented For Model Development*

Relevant literature reveals that current AI/ML forecasting models suffer from a multitude of issues. For instance - Autoregressive Integrated Moving Average (ARIMA) struggles in capturing external insights influencing carbon prices [13]. Similarly, Long Short-Term Memory (LSTM) struggles with daily prices, offering both low value interpretability and optimum forecasting stability [14]. Hence to develop our proposed framework, two techniques were chosen for integration - DCGAN and XAI owing to the benefits they brought forth in the context of our study. This is because DCGAN is found to improve time-series forecast through use of deep convolutional layers for better data augmentation [15]. Similarly, XAI was found to bring multiple benefits in the context of improving model interpretation as it provides data backed insights regarding the overall influence both the internal and external features considered have over the predicted price [16]. Fig 1 showcases the flowchart depicting the methodology adopted for model development and Fig 2 showcases the DCGAN Model Architecture devised.

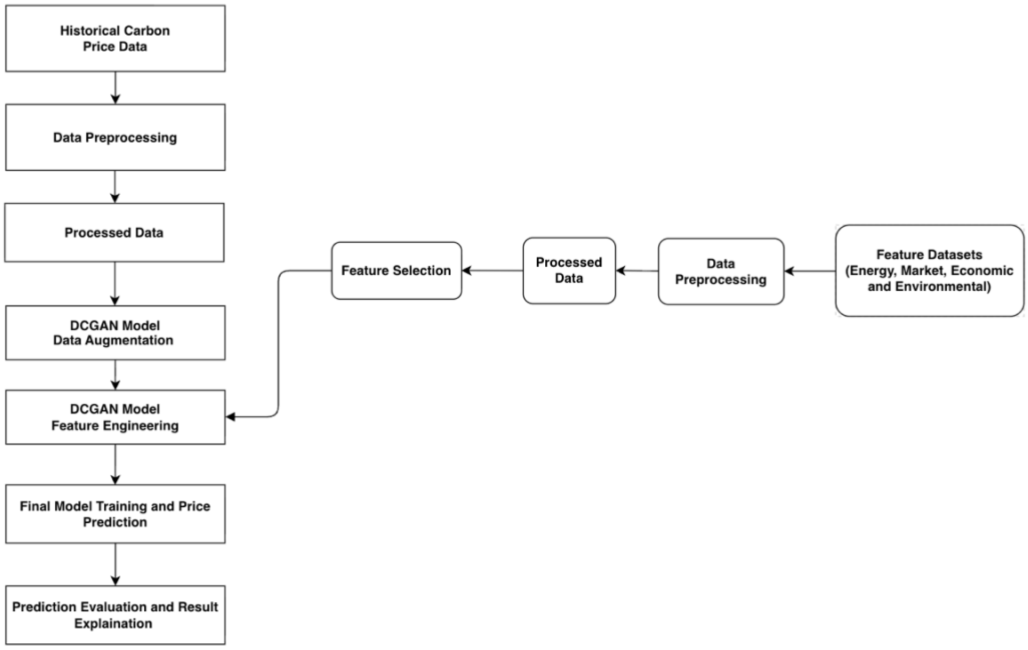

Fig 1. Methodology Adopted for Price Forecasting Framework Development

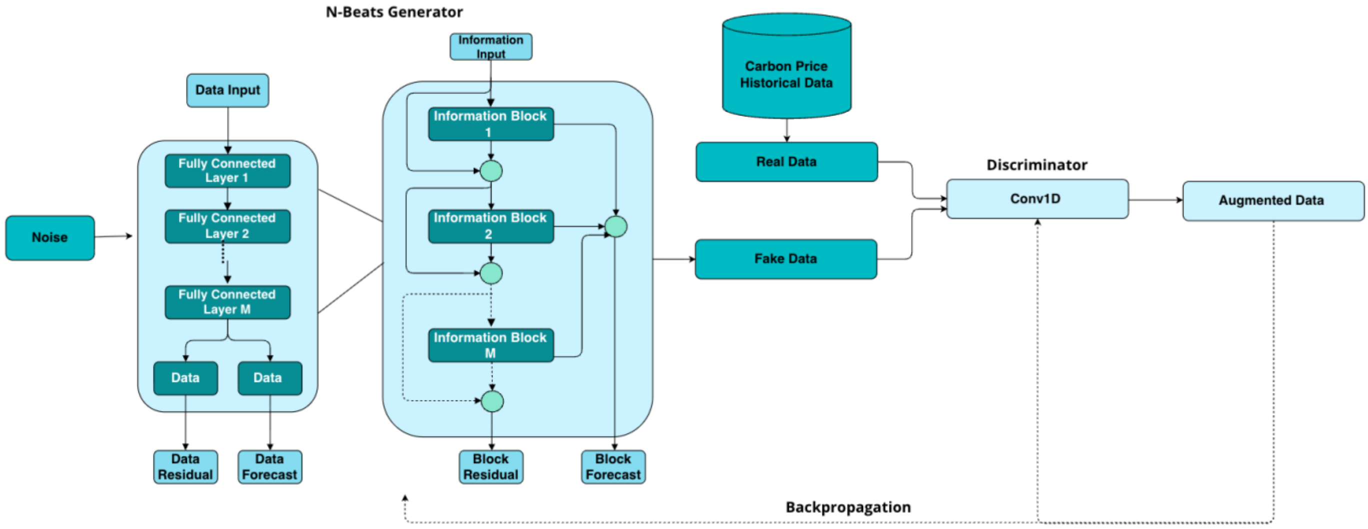

Fig 2. DCGAN Architecture developed for interpretable carbon price forecasting

The Neural Basis Expansion Analysis for Time Series (N-Beats) framework was integrated as the Generator for our DCGAN model. This technique was chosen due to its ability to capture data trends and long-term relationships, effective information management along with providing better insight interpretability when compared to LSTM and other neural networks [17].

$$h_b = ReLU\left(W_l \cdot ReLU\left(W_{l-1} \cdots ReLU(W_1 x_b)\right)\right)$$

$$\theta_b = W_\theta \theta_b, \ \theta \in R^{2T}$$

$$\theta_b = [backcast_b | \, forecast_b], \qquad each \in R^T$$

$$y = \sigma(W_c \cdot [forecast_1 \cdots forecast_b])$$

Similarly, 1D Convolution Layer (Conv1D) was integrated as our DCGAN's discriminator to assist with data validation. We opted to use this technique owing to its ability to recognize frequently emerging patterns within time series datasets, provide faster training speeds, offers stable training cycles and providing realistic results [18].

$$h_1 = LeakyReLU(Conv1D(x; W_1, k = 5, s = 1, p = 2))$$

$$h_2 = LeakyReLU(Conv1D(h_1; W_2, k = 5, s = 1, p = 2))$$

$$h_3 = LeakyReLU(W_3 \cdot vec(h_2)), \ W_3 \in R^{256\times(64T)}$$

$$D(x) = \sigma(W_4 \cdot h_3), \ \ W_4 \in R^{1\times256}$$

$$\min_G \max_D E_{x\sim p_{data}}[\log D(x)] + E_{z\sim p_z}[\log(1 - D(G(z))]$$

This was followed by implementation of Random Forest as both the feature selection mechanism and the prediction system for our model. It offers independent feature importance precedence selection and being computationally faster, provide robust predictions, improve forecast interpretability, better management of complex data and faster performance compared to similar techniques [19].

$$y(x) = \frac{1}{M}\sum_{m=1}^{M} T_m(x)$$

$$\min_{j,r}[MSE_{left} + MSE_{right}]$$

$$I_j = \sum_{t \in splits\ on\ j} p(t)\Delta MSE(t)$$

Finally, for integrating XAI into our model, we implemented Shapley Additive Explanations (SHAP) for achieving model interpretability [20].

$$\phi_j(f,x) = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!\,(|F|-|S|-1)!}{|F|!}[f_s(x_s \cup \{j\}) - f_s(x_s)]$$

$$\phi_j = \sum_{T \in ensemble} \sum_{l \in leaves\ of\ T} \Delta l_j \cdot w_l \ (for\ tree\ val)$$

B. Datasets Considered and Data Processing

For our primary forecast dataset, we opted to use the Hubei ETS Historical Transaction Dataset. It is one of the eight regional ETS systems established in the first phase of China's national carbon market development. First operated in 2014, it is known for its high-grade stability and strong industrial diversity, which helped it to emerge as the forefront framework for shaping up China's National ETS market as well [21]. For this study, Hubei ETS was not only chosen based on its benefits but also based on two major aspects - Compared to other regional ETS systems like Beijing and Guandong and National ETS like China ETS it showcases a higher degree of market freedom and is far more mature in terms of its sectoral focus and price allocation [22]. In comparison to EU ETS, it is relatively simpler in its market structure, as it relied more on sectoral dependencies within its region alongside govt. initiatives [23]. Additionally, it made sense to choose Hubei ETS, as its forecasting insights could help towards developing India's upcoming Carbon Credit Trading Scheme (CCTS). Like China which ran Hubei ETS as regional pilot program, India also currently runs its pilot ETS program, the Perform, Achieve and Trade (PAT) scheme. Thus, Hubei ETS tends to serve as a benchmark narrative to understand how carbon markets behave on a regional level, something that the India's upcoming plan would greatly benefit from as it expands its coverage from sectoral to national level emission management [24].

The forecast dataset was acquired from the official Hubei carbon emission exchange website [25]. We acquired data of daily price frequency for the last 8 years between 05th April 2017 to 30th September 2025. For ensuring resilient forecasting, the forecasting features for the dataset were considered using the OHLC framework - leading us to consider parameters like Open, High, Low and Close prices alongside other parameters like volume, transaction amount and price rise-fall. Table 1 gives us insights related to the data values observed within our price dataset relevant to our research.

TABLE 1 FORECAST DATA STATISTICS

Name	Value
Maximum Price	61.48
Minimum Price	11.56
Average Price	34.22
Std Dev.	10.99

Additionally, the Fig 3 below showcases the trend of carbon price allowance considered (Hubei Emission Allowance (HBEA) between the considered time period.

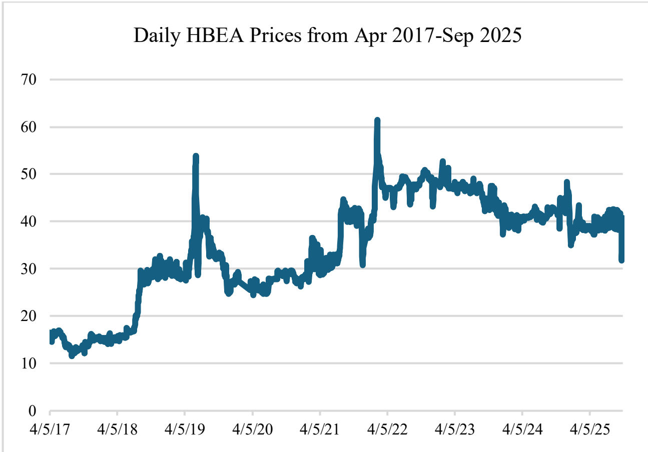

Fig 3. Prices observed for HBEA during the considered collection period

Alongside our forecast dataset, we considered 8 other datasets across 4 factors for feature engineering based on relevant literature to ensure that our model offers results that are reliable and explainable from a market perspective based on relevant literature [26]. All datasets followed the same time period of daily data frequency as the forecast dataset for the sake of homogeneity and were obtained from open-source trading websites and repositories. Table 2 showcases the features considered alongside the datasets chosen -

TABLE 2 FEATURE DATASET INFORMATION

Feature	Value	Dataset Considered
Feature 1	Energy-Centric Commodities	WTI Crude Oil [27]
		Natural Gas Futures [28]
Feature 2	Market Indexes	S&P 500 Index [29]
		NASDAQ 100 Index [30]
Feature 3	Economic Indicators	Volatility Index (VIX) [31]
		Nominal Broad US Dollar Index (DTWEXBGS) [32]
Feature 4	Environmental Factors	Average PM 2.5 [33]
		Daily Temperature [34]

For ensuring resilient price prediction several data processing steps were undertaken like non-price feature data imputation through linear interpolation, implementing a train test split of 80:20 for both feature selection and price forecasting along with implementation of 30-day rolling windows and its subsequent values for driving final price forecasts so as to preserve temporal features and to improve prediction accuracy.

III. RESULTS OBTAINED AND PRICE INTERPRETATION

After developing our forecasting model and engaging in the process of price prediction using it over our chosen dataset, the final step is to evaluate the results derived. In accordance with our objectives, the result has been obtained in 2 different ways - firstly, we have acquired our model's performance metrics in a numeric manner to comparatively analyse our model's performance against other models of similar kind. To analyze and deduce how our model fared in comparison to other published studies, we considered three benchmark values - Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). RMSE is a metric utilized to calculate the standard deviation achieved by an error. MAPE is used to calculate the absolute percentage difference between predicted values and the actual value. MAE is used to calculate the absolute difference between the predicted and actual values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \dot{y}_i)^2}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \dot{y}_i}{y_i}\right|$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \dot{y}_i|$$

As we can see in Table 3, we compared our model's metrics with other forecasting models developed and tested over Hubei ETS, other regional ETS, China National ETS and EU ETS. We chose to compare our metrics to both historic models developed and recent models developed so as to effectively analyze how our model fares compared to historic implementations and recent forecasting endeavor. As our model is a hybrid mixture of DCGAN with multiple neural networks and tree-based models, we chose to compare our model with other forecasting architecture that adopts either neural network-based architecture, hybrid architecture or GAN-based architecture for effective comparison and result reporting.

TABLE 3 COMPARISON OF THE HYBRID DCGAN MODEL RESULT WITH OTHER PUBLISHED MODELS

Study	ETS considered	Model Used	RMSE	MAPE	MAE
[35]	Hubei ETS (2015-18)	PSO-LSSVM	2.01	6.74	1.79
		BA-LSSVM	2.36	7.15	1.81
		LSSVM	3.10	9.01	2.46
	Hubei ETS (2016-18)	PSO-LSSVM	3.12	8.44	1.36
		BA-LSSVM	2.68	8.56	2.41
	Hubei ETS (2017-18)	PSO-LSSVM	2.81	8.44	1.36
		BA-LSSVM	2.68	8.56	2.41
[36]	Hubei ETS	BP	1.98	5.19	1.61
	Beijing	ELM	3.18	2.23	1.67
		ICEEMDAN-PSR-BP	2.84	2.52	1.99
	Guangdong ETS	BP	1.97	5.93	1.67
[37]	China National ETS	GRU-CNN-LSTM	4	4.38	3.62
		GRU-CNN-LSTM-BO	2.53	2.31	1.94
	EU ETS	GRU-CNN-LSTM	1.87	1.75	1.46
		GRU-CNN-LSTM-BO	1.70	1.66	1.38
[38]	Beijing ETS	CPFNet	5.34	10.5	3.59
	Tianjin ETS	CPFNet	3.02	11.6	1.96
	Shanghai ETS	CPFNet	1.74	2.10	1.07
	Chongqing ETS	CPFNet	1.76	6.6	1.29
Our Study	**Hubei ETS**	**DCGAN-NBeats-Conv1D-RF**	**1.17**	**2.27**	**0.92**

Apart from this, we also considered GAN training loss graph and RF next day forecast vs actual to validate our model performance. As we can see in Fig 4. the GAN training loss appears to be stable and showcases expected normal behavior, which translates to our model effectively engaging in data augmentation and training. Similarly, in Fig 5, the RF forecast vs actual graph showcases that our model is able to achieve predicted price values closer to the actual value, validating the forecasting accuracy.

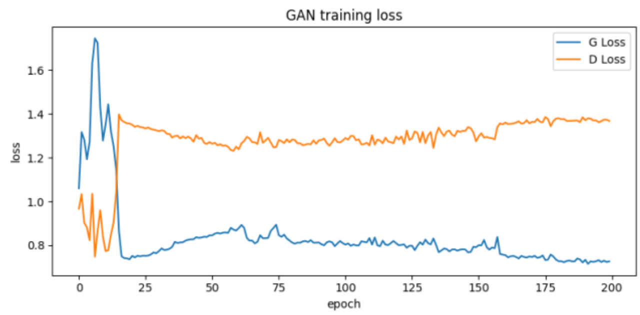

Fig 4. GAN Training Loss Graph Observed for our model

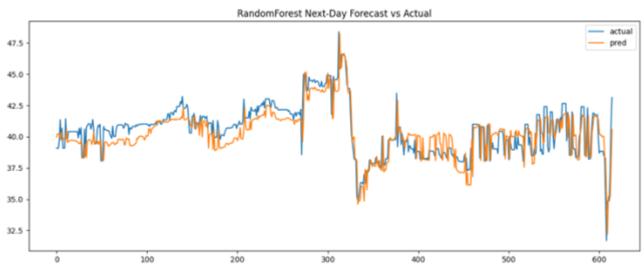

Fig 5. Forecast vs Actual Price Graph for our model using RF

To interpret the feature importance considered by our model during price prediction we have constructed both SHAP bar charts and bee swarm plots to showcase impact magnitude and relationship dynamics. As observed in Fig 6, the latest value observed for HBEA's daily closing price in the last 30 days (Close_last) was interpreted to be the most influential factor, owing to its immense value of impact over model output magnitude (over 10) which directly translates to it having the biggest impact over price prediction in case of one day-ahead price forecasting.

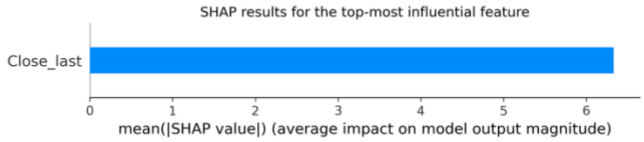

Fig 6. SHAP Bar Chart of magnitude of average impact on price for the top feature

As observed in Fig 7, the other remaining 25 selected features have relatively low impact values compared to the top-most parameter (between 0.005 and 0.5), which meant that they did not have that big of impact on day-ahead predicted prices as that of the top-most feature. However, this does not imply that the features were by themselves useless or did not play any role towards influencing carbon prices. The very presence of non-zero values in the SHAP plots displays that there is a relationship exhibited between the prices predicted and the features considered. What this means is that whilst their influence on short-term forecasting may appear minimal, but they are still important, as they emerge to be excellent explanatory indicators for the prices forecasted. These thereby act as secondary constructs that could be enforced in case of extraordinary circumstances emerge (regime change, new policies introduced etc.) to ensure correct prices are predicted, nonetheless.

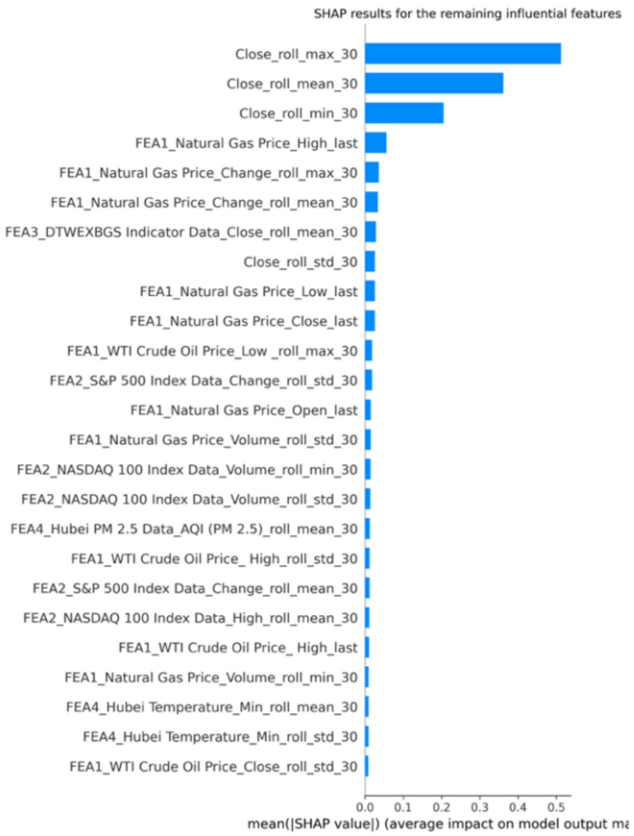

Fig 7. SHAP Bar Chart of magnitude of average impact on price for the remaining features

The SHAP bee swarm reflect the nature of relationship between features and the price predicted with red signifying higher values, purple signifying neutral values and blue signifying negative value. In the case of the topmost feature, as seen in Fig 8- the latest value observed for HBEA's daily closing price in the last 30 days (Close_last) has a direct relationship, as its reports red on positive end, indicating that its higher values drive higher carbon prices.

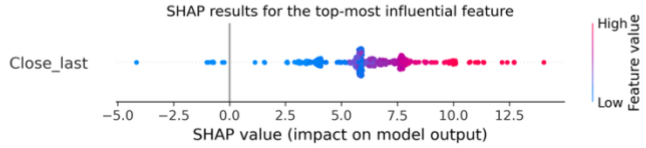

Fig 6. Bee Swarm Chart depicting relationship interpreted between impact and price for the top feature

For rest 25 features as seen in Fig 9, we see different correlations arising, like the latest value observed for Natural Gas's daily high price in the last 30 days (FEA1_Natural Gas Price_High_Last) effect on the price predicted depends on the value achieved as depicted by its majority purple values near zero, meaning that the predicted price does not rise or fall based on this parameter's rise or fall, it is more of context-specific dependency. Similarly, the standard deviation observed for S&P 500's daily Change parameter in the last 30 days (FEA2_S&P 500_Index Data_Change_roll_std_30) has a direct relationship with the price predicted as it reports blue on the negative end, indicating that its lower values drive lower carbon prices. However, there are instances wherein inverse relationship is observed. For instance, the standard deviation observed for WTI Crude Oil's daily High Price in the last 30 days (FEA1_WTI Crude Oil Price_High_roll_std_30) has an inverse relationship as it reports red on the negative end, indicating that its higher value drives lower carbon prices. Finally, the standard deviation observed for Hubei Temperature's daily minimum value in the last 30 days has an inverse relationship as it reports blue on positive end indicating that its lower value drives higher carbon prices.

Fig 7. Bee Swarm Chart of relationship between impact and predicted price for remaining features

IV. Conclusion

In past few years, there is urgent need for companies to tackle emissions produced so as to protect the environment. Whilst concrete initiatives have been taken such as ETS and CE practices, roadblocks emerge in terms of their individual and integrated application owing to issues pertaining to integration of AI-centric methods. To mitigate the gaps realized, a novel hybrid DCGAN-XAI carbon price forecasting model was proposed to derive interpretable carbon prices. Whilst our study showcases a promising use for the model developed based on the findings interpreted from the results, a scope for further improving the model is realized. Future work plans involve integrating optimization techniques for improving model performance, utilizing other frameworks within the DCGAN model etc.

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