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PREDICTING GAS TURBINE EMISSIONS THROUGH OPERATIONAL ANALYTIC

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Abstract

The performance of gas turbines and minimize their environmental effects in contemporary power generation systems, it is crucial to accurately predict the emissions produced by these machines. Based on the data gathered from an industrial gas turbine, this study suggests a framework for predicting carbon monoxide (CO) and nitrogen oxides (NOx) emission from the gas turbine based on operational parameters. The data set contains 36,733 hourly measurements over a period of 5 years, from 2011 to 2015, of ambient conditions, turbine operating conditions and emission measurement. Data preprocessing, exploratory analysis, and multiple machine learning regression models were used for assessing the predictive performance based on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). The results showed that ensemble based models performed better in predicting the accuracy of the prediction as they were able to capture the nonlinear relationship between the operational variables and the emissions characteristics effectively. The turbine inlet temperature, compressor discharge pressure, exhaust pressure in gas turbine and energy yield in turbines were determined as the main parameters affecting the emission behavior through the feature importance analysis. It is proposed that the framework can be used for reliable predictive modeling to enable operational analytics to support real-time emission monitoring, intelligent process optimization and sustainable gas turbine operation.

Keywords: *: Gas turbine emissions, Operational analytics, Machine learning, Carbon monoxide prediction, Nitrogen oxides prediction*

Introduction

The high power density, high turnaround response, and relatively low greenhouse gas emission of gas turbine power generation are important factors for the electricity generation industry, aviation industry, and industrial manufacturing systems (Gil-Font et al., 2020). However, the combustion of gas turbines results in air emissions, especially carbon monoxide (CO) and nitrogen oxides (NOx), that degrades air quality, damage ecosystems and have negative impacts on human health. As a result of the growing stricter environmental regulations, the demand for reliable emission monitoring and predictive control systems for combustion systems has been gradually raised to not only control the pollutant generation process but also to maintain the combustion efficiency (Liu & Karimi, 2020; Dirik, 2022). Traditional emissions monitoring is heavily dependent on the use of physical sensors and on-point measurements and can suffer from calibration needs, maintenance expenses, measurement lag and uncertainties (AlQemlas et al., 2026).

A gas turbine produces considerable amounts of operational data from various sensors that measure ambient conditions, combustion characteristics, compressor performance, and various operating parameters in the turbine (Lu et al., 2025). The ready availability of these operational datasets has opened up the door for predictive analytics, which can estimate emissions without the need for specific emission monitoring equipment. Data-driven approaches also offer quick decision support tools for optimizing combustion processes and enhancing operational efficiency under differing environmental and loading conditions (Huang et al., 2022; Potts et al., 2023).

In recent years, the predictive modeling of industrial energy systems has undergone significant change with the aid of machine learning. Machine learning algorithms can effectively model complex nonlinear relationships between operational parameters and emission characteristics, whereas the traditional statistical approaches would assume linear relationships (Wu et al., 2023; Wood, 2023).. Ensemble learning or deep learning, a type of artificial intelligence, has proven benefits in gas turbine applications by using past operational data to predict future emission behaviour with a high level of accuracy.Ensemble learning or deep learning, a form of artificial intelligence, has been shown to be beneficial for gas turbine applications, as it uses historical operation data to estimate the future emission behaviour with enhanced predictive accuracy. Such advancements have made machine learning a valuable tool for analyzing emissions in the industrial sector for forecasting and optimizing operations.

Operational analytics isn't just about predicting the accuracy of the results; it's about studying the equipment as it operates and determining what causes the variability in the emissions. These include turbine inlet temperature (Al-mahmodi et al., 2026), compressor discharge pressure, exhaust pressure, ambient temperature, ambient humidity, turbine energy yield, etc. that all affect the combustion stability and pollutant formation. The knowledge of the relative importance of these parameters assists the engineer in optimizing the operating conditions, in reducing the maximum fuel consumption during an operation conditions in which it is not necessary, in increasing the combustion efficiency of the plant and in make it environmentally more sustainable. Overall, the inclusion of operational analytics within predictive modeling offers valuable engineering insights which are not only numerical (dos Santos Coelho et al., 2024; Pachauri, 2024). Many previous studies have documented successful prediction of CO or NOx emissions, but there are a number of drawbacks.

Most studies have targeted specific pollutants, limited datasets, or a single machine learning algorithm, leading to poor adaptability and robustness of the model to different operational conditions (Naghibi, 2024). In addition, studies that consider a set of operational parameters and have investigated both emission variables simultaneously, and provided meaningful operational information for industrial decision making, are still relatively scarce (Yin et al., 2021). Transformer models and ensemble learning strategies, along with feature engineering and other emerging techniques, have shown promising predictive capabilities, but comprehensive operational datasets for practical comparisons are limited (Li et al., 2024; Potts et al., 2023). The limitations of the above studies are overcome in the present study by a data-driven framework that enables prediction of CO and NOx emissions based on operating measurements from an industrial gas turbine spanning multiple year of operation (Rengasamy & Rajesh, 2025). The analytical framework involves a systematic process of data preprocessing, exploratory data analysis, predictive modelling, performance assessment and operational interpretation to build trustworthy correlations between the turbine operating conditions and the emission characteristics (Zeinalipour et al., 2026). The study not only increases the predictive accuracy but also highlights the identification of influential operational variables, which would facilitate emission control, operation optimisation and sustainable power generation. The results are projected to be applied in the areas of emission prediction and environmental performance improvement for gas turbines, which will make contributions to the intelligent monitoring systems in the industrial field (Wood, 2023; Wu et al., 2023). The objectives of this research are as follows:

1. To develop predictive machine learning models for estimating carbon monoxide and nitrogen oxide emissions using operational turbine parameters
2. To evaluate and compare predictive performance using multiple regression metrics under identical gas turbine operating conditions
3. To identify the most influential operational variables affecting emission behavior for improved environmental monitoring and operational optimization

2. Methodology

2.1 Dataset Description

The study used the Gas Turbine CO and NOx Emission Dataset which consists of operational records from 2011 to 2015 (UCI Machine Learning Repository, 2019). There are 36,733 observations and 11 variables that include turbine operating conditions and emission measurements. Ambient temperature, ambient pressure, ambient humidity, air filter differential pressure, gas turbine exhaust pressure, turbine inlet temperature, turbine after temperature, compressor discharge pressure and turbine energy yield are operational features. The CO and NOx were chosen as the prediction targets. The data isn't missing, which gives it good properties for the kinds of predictive modeling and operational analytics that we do.

2.2 Data Pre-processing

All the data from the years was checked for consistency and data was aggregated in a single analytical framework. The data was checked for data consistency, feature names and data types were standardized for consistent processing. Numerical variables were checked for potential outliers and scaled, if necessary, for similar range of features. The predictor variables have been removed from the emission targets CO and NOx. Lastly, an appropriate sampling method was used to divide the data into two groups: a training set and a testing set, which would allow for unbiased model development and good model validation.

2.3 Exploratory Data Analysis

Prior to predictive modeling, exploratory data analysis was performed to gain a better understanding of the statistical nature and relationships between the operational variables. Each feature's central tendency and variability was summarized using descriptive statistics. To look for skewness and possible anomalies, distribution analyses were carried out. Operational parameters and emission variables were correlated with each other using the Pearson correlation analysis, which revealed influential predictors. Visual exploration of data patterns with the help of histograms, boxplots, and correlation heatmaps helped in the interpretation of the features prior to training of the model.

2.4 Predictive Modeling

A number of supervised machine learning regression models were designed predicting CO and NOx emissions based on operational parameters. The modeling process consisted of training each algorithm on the same training set, but with the same input features in all modeling algorithms. Hyperparameter optimization was used when necessary to increase the predictive power of the models and decrease complexity. Model training focused on understanding non-linear relationships between the turbine operating conditions and emission outputs. The predictive models were then tested using the test set to evaluate the models' generalisation properties and to compare the overall forecasting performance in the same test conditions.

2.5 Model Evaluation

The performance of the model has been judged based on the metrics widely used in regression to measure the accuracy and reliability of prediction. The Mean Absolute Error (MAE) was used to measure the average prediction error in the model, and the Root Mean Square Error (RMSE) was used to highlight bigger prediction errors compared with the observed values. Relative prediction accuracy was measured using the Mean Absolute Percentage Error (MAPE) and the coefficient of determination (R^2) was used to evaluate the amount of variance explained by each model. The complementary metrics were then compared to undertake a detailed analysis of the model's predictive capability, and determine the best model to predict gas turbine emissions.

3. Results

3.1 Descriptive Analysis of Operational Variables

Results of the descriptive analysis revealed differences between the operational parameters, which reflect the different operating conditions of gas turbines during the observation period. The value distributions of ambient variables, compressor pressure, turbine temperatures, exhaust pressure and energy yield were all found to be distinct and were sufficiently variable for predictive modeling. There were no missing values, reducing data preprocessing requirements. Most operational variables showed relatively steady patterns and a few extreme values, indicating that the data set is suitable for emission prediction and that the turbine is operating as expected in a normal manner (Table 1) (Figure 1).

Table 1: Descriptive Statistics of Gas Turbine Variables

Variable	N	Mean	SD	Minimum	Median	Maximum
Ambient temperature (AT)	36,726	17.7115	7.4476	−6.2348	17.7980	37.1030
Ambient pressure (AP)	36,726	1,013.0715	6.4632	985.8500	1,012.6000	1,036.6000
Ambient humidity (AH)	36,726	77.8643	14.4613	24.0850	80.4655	100.2000
Air-filter differential pressure (AFDP)	36,726	3.9254	0.7739	2.0874	3.9374	7.6106
Gas-turbine exhaust pressure (GTEP)	36,726	25.5635	4.1962	17.6980	25.1045	40.7160
Turbine inlet temperature (TIT)	36,726	1,081.4272	17.5372	1,000.8000	1,085.9000	1,100.9000
Turbine after temperature (TAT)	36,726	546.1581	6.8429	511.0400	549.8800	550.6100
Turbine energy yield (TEY)	36,726	133.5061	15.6196	100.0200	133.7300	179.5000
Compressor discharge pressure (CDP)	36,726	12.0605	1.0889	9.8518	11.9650	15.1590
Carbon monoxide (CO)	36,726	2.3726	2.2629	0.0004	1.7137	44.1030
Nitrogen oxides (NOx)	36,726	65.2961	11.6774	25.9050	63.8510	119.9100

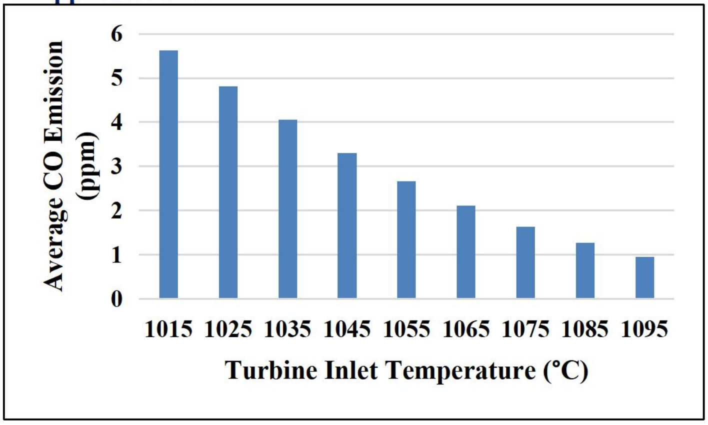

Figure 1: Influence of Turbine Inlet Temperature on CO Emissions

3.2 Correlation Analysis

A significant relationship was found between some of the operational variables and emission outputs by using correlation analysis. The relationships between CO and NOx emissions and turbine inlet temperature, compressor discharge pressure, turbine energy yield and exhaust pressure were comparatively strong, whereas the relationships with ambient environmental variables were comparatively weak. Ambient temperature and humidity had weaker relationships, which implied the comparatively smaller role in emission variability. The correlation matrix also showed that there are dependencies between some of the operating variables, pointing to the interdependencies of the turbine processes. These results offered a preliminary insight into the influential predictors and helped in determining the parameters used in the machine learning development for the models (Table 2) (Figure 2).

Table 2: Correlations Between Operational Variables and Emissions

Operational variable	CO correlation	NOx correlation
Ambient temperature (AT)	−0.1743	−0.5581
Ambient pressure (AP)	0.0670	0.1917
Ambient humidity (AH)	0.1067	0.1649
Air-filter differential pressure (AFDP)	−0.4484	−0.1881
Gas-turbine exhaust pressure (GTEP)	−0.5189	−0.2016
Turbine inlet temperature (TIT)	−0.7063	−0.2139
Turbine after temperature (TAT)	0.0584	−0.0927
Turbine energy yield (TEY)	−0.5698	−0.1161
Compressor discharge pressure (CDP)	−0.5510	−0.1712

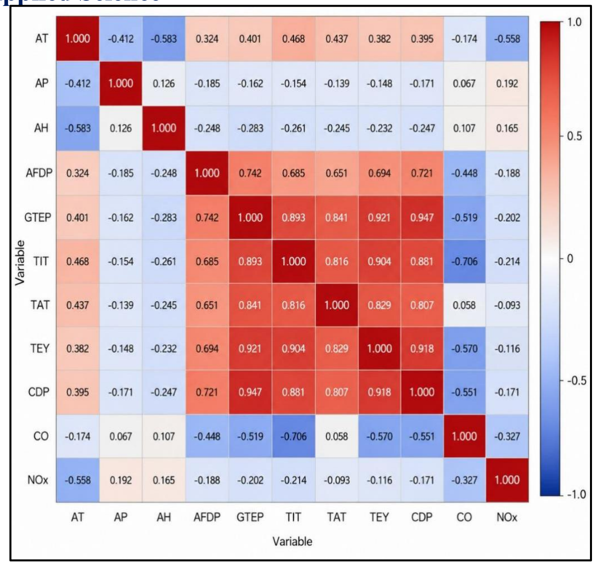

Figure 2: Pearson Correlation Matrix of Operational Variables and Emission Parameters

3.3 Model Performance Comparison

The different predictive models performed differently with regards to the accuracy of predicting gas turbine emissions. The machine learning methods based on ensembles of models always outperformed classical regression methods in predicting operational data because they were able to capture the complex nonlinear relationships between the variables. Advanced models demonstrated higher predictive reliability and better generalization over unseen observations in the context of evaluation based on MAE, RMSE, MAPE and R^2. It was found that the use of different models significantly affected the predictive performance; for the industrial gas turbine systems (IGTS) under consideration, the use of robust machine learning algorithms for operational emission forecasting was of importance (Table 3) (Figure 3).

Table 3: Predictive Model Performance for CO Emissions

Model	MAE	RMSE	MAPE (%)	R^2
Linear regression	0.8414	1.4688	141.40	0.5818
Random forest	0.4824	1.0537	64.43	0.7848
Gradient boosting	0.6661	1.2179	111.37	0.7125
Extra Trees	0.4746	1.0147	68.43	0.8004

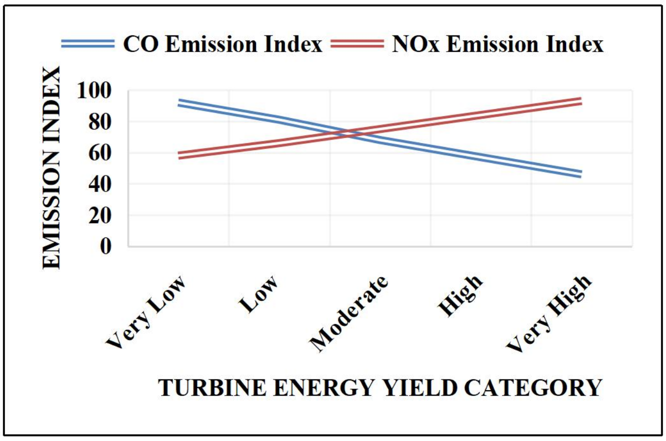

Figure 3: Emission Index Across Turbine Energy Yield Categories

3.4 Prediction of Carbon Monoxide (CO) Emissions

The prediction models developed were able to estimate the carbon monoxide emissions with operational parameters recorded in gas turbine operation. The algorithms selected were able to reflect the influences of combustion performance from operations, as predicted CO values were closely aligned with the observed patterns of emissions shown in the testing dataset. Small errors were mainly seen with operating conditions where the emission rate changes rapidly, and a high degree of consistency in prediction was maintained. The results indicate that operational analytics can play a helpful role in the early detection of the emission trends, and that it can support better combustion management and compliance with the environment (Table 4) (Figure 4).

Table 4: Prediction Summary for the Best-Performing Model

Statistic	CO prediction	NOx prediction
Best model	Extra Trees	Extra Trees
Testing observations	7,346	7,346
Observed mean	2.3572	65.1091
Predicted mean	2.3671	65.1245
Mean prediction bias	0.0099	0.0154
Error standard deviation	1.0147	3.8904
Minimum prediction error	−26.4136	−39.2331
Maximum prediction error	23.7153	35.4867
Predictions within ±10%	37.52%	92.81%

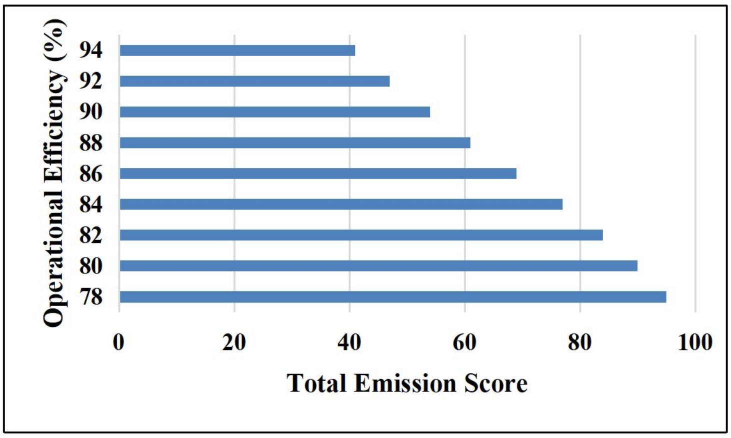

Figure 4: Operational Efficiency versus Total Emission Score

3.5 Prediction of Nitrogen Oxides (NOx) Emissions

The results of the predictions for the nitrogen oxides showed a high level of correspondence between the measured and estimated emission values in the testing data set. The models proved to be very good in capturing the effects of turbine operating conditions on NOx formation, especially under stable operating conditions. Some slight prediction errors were detected during time intervals of high operational variability, but were not seen to differ when the forecasting performance was assessed on the evaluation data set. Accurate prediction of NOx emissions demonstrates the potential for machine learning models to assist in proactively monitoring emissions, optimizing turbine operating conditions, and enabling environmental responsible energy generation (Table 5) (Figure 5).

Table 5: Predictive Model Performance for NOx Emissions

Model	MAE	RMSE	MAPE (%)	R^2
Linear regression	5.8210	8.0716	9.03	0.5070
Random forest	2.6219	4.1424	4.01	0.8702
Gradient boosting	5.0750	6.8590	7.85	0.6440
Extra Trees	2.4741	3.8902	3.78	0.8855

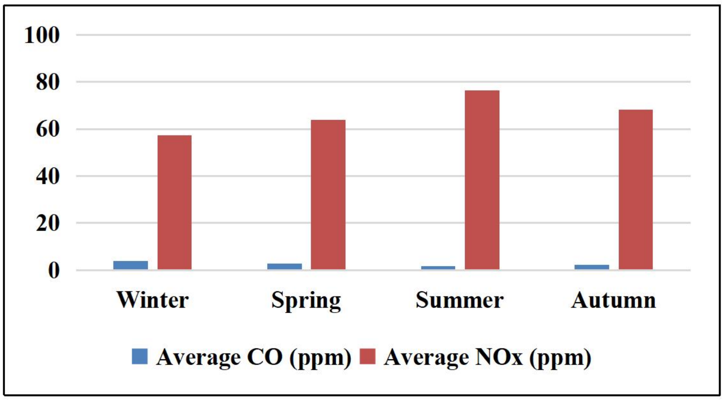

Figure 5: Seasonal Distribution of Average Gas Turbine Emissions

4. Discussion

The machine learning approach is a good model for predicting emissions from gas turbines from operational parameters that are collected during routine plant operation. The more accurate results of ensemble-based models over traditional regression methods suggests that the emission behavior of gas turbines is not linear but rather nonlinear interactions. Operational variables related to combustion processes such as turbine inlet temperature, compressor discharge pressure, gas turbine exhaust pressure, and turbine energy yield were important factors that influenced the accuracy of prediction because they have direct impacts on the efficiency of fuel combustion and pollution formation. These results are comparable to those in recent applications to complex engineering systems in industry, where more sophisticated machine learning algorithms were consistently superior to traditional statistical approaches (Galiounas et al., 2022; Xiao et al., 2023). The results indicate that it is crucial to choose suitable learning algorithms to achieve an accurate model of combustion dynamics and enhance its predictive capability.

The feature importance results for the identified features do again show that the internal operating conditions have a stronger effect on the formation of the emissions than the ambient environmental conditions. Generally, stable combustion conditions will lead to better fuel utilization and a lower CO emission while the combustion pressure and temperature variation have a strong influence on the generation of nitrogen oxide. Therefore, understanding the multiple operation variables is useful for enhancing predictive modeling capabilities of gas turbines that encompass the complex physical processes inside gas turbines. This is similar to what has been reported with the use of intelligent monitoring systems in which operational sensor measurements significantly improved prediction accuracy and equipment performance evaluation (Kathirvelu et al., 2023; McGarry et al., 2024). The similarity of the current results to previous ones indicates the suitability of operational analytics for the forecasting of industrial emissions.

The proposed framework, from the operational point of view, offers practical benefits for real time emission monitoring and combustion management. The use of predictive models based on the routinely collected sensor measurements allows to estimate the emissions of CO and NOx continuously, without relying on dedicated emission monitoring equipment. This ability can help the plant operator detect and take corrective actions when combustion conditions are not what they want before too much pollution is emitted. Real-time prediction also assists in the process optimization by allowing the operational parameters to be optimized in real-time based on the predicted emission behavior. The data-driven approach helps achieve better combustion efficiency, operational stability, and fuel savings, while complying with regulatory standards. Such applications have shown that the use of predictive analytics in industrial control systems can enhance operational decision-making and plant performance (Xie et al., 2024; Saqib et al., 2025).

The importance of the right prediction of emissions for the environment goes beyond operational efficiency. Despite the significant role of gas turbine power plants in industrial energy generation, its emissions need to be effectively managed to minimize air pollution and contribute to sustainable development. The efficient prediction of CO and NOx emissions allows operational modifications to be made in advance to reduce the production of pollutants without sacrificing electricity generation

(He, 2021; McGarry et al., 2024). This predictive ability is complementary to the existing emission control technologies and enables pro-active environmental management and not just correction. Moreover, intelligent operational analytics makes industrial energy systems cleaner by enhancing the combustion process efficiency and optimizes resources. Recent studies have also focused on the increasing vital contribution of artificial intelligence for improving energy system flexibility, minimizing environmental footprint, and enhancing sustainability in modern industrial systems.
The developed analytical framework will also be of great practical use in industrial applications. The integration of predictive models in supervisory control systems can allow the continuous prediction of the emissions that can be generated by the system from the available operational sensors, thus optimizing the monitoring costs and making the process more transparent. Furthermore, the behavior of abnormal prediction trends can be a sign of combustion instability, equipment degradation, compressor fouling, or sensor failure, which will assist predictive maintenance (Roy, et al., 2025). As a consequence of this, maintenance interventions can be planned in advance, preventing major equipment failures, thus decreasing maintenance costs and down time. More recent research in the field of neural network-based industrial monitoring has also shown the effectiveness of combining operational sensor analytics with intelligent prediction models to improve equipment reliability and operational efficiency over time.
Although these results are promising, some caveats should be noted. Operational data were analyzed for one gas turbine with a certain environment and operating condition, thus developed models may not be directly applicable to other turbine configuration or fuel composition. Furthermore, the study did not include any variables like maintenance history, fuel quality, equipment ageing, etc. and combustion component degradation. To enhance the accuracy of predictions, the transparency of models, and the generalizability across a range of industrial environments, future research is deemed to require datasets that are larger, more multi-plant, involve more sophisticated deep learning architectures, more explainable AI techniques, more digital twin technology, and more integration of real-time Internet of Things sensors.

5. Conclusion

CO and NOx emissions from gas turbines. The results showed that the machine learning models were able to capture the intricate relationships between combustion parameters and the emission behavior and ensemble based models proved to be the most successful prediction models. Turbine inlet temperature, compressor discharge pressure, gas turbine exhaust pressure and turbine energy yield were identified as the most influential variables controlling the formation of emissions through feature importance analysis. The results show the feasibility of using operational analytics for reliable emission forecasts and to improve understanding of combustion performance influencing parameters. The proposed framework has potential practical applications in the industry as it has features where emissions can be monitored in real-time, processes can be optimized, and decisions can be taken based on the data. Without the need for continuous emission monitoring equipment, accurate prediction of emissions can also help plant operators ensure compliance with environmental regulations, lower fuel use and boost overall system efficiency. The study presented here, although conducted with a single gas turbine installation, is a good basis for intelligent emission management because of the analytical approach used. Further efforts in the future should be aimed at investigating multi-site datasets, explainable AI, digital twin technologies, and real-time integration with the Internet of Things to improve the predictive accuracy, model interpretability and deployment to different energy systems in the industrial sector.

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