TRANSPORT PROBLEMS 2025 Volume 20 Issue 3
PROBLEMY TRANSPORTU DOI: 10.20858/tp.2025.20.3.09

Keywords: SAF; ADS-B; aviation emissions; ICAO EEDB; machine learning

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NEW MACHINE LEARNING MODEL FOR PREDICTING AIRCRAFT EMISSIONS BASED ON ENGINE, OPERATIONAL PARAMETERS, AND FUEL PROPERTIES

Summary. With growing environmental concerns surrounding it, all efforts in the aviation sector are moving toward reducing the ecological footprint of this sector. One of the promising solutions is sustainable aviation fuel, which offers an alternative to traditional jet fuel. This study investigates the possibility of using a developed machine learning model designed to forecast aircraft emissions using a set of 11 inputs related to engine specifications, fuel properties, and ambient air conditions. The model is trained based on version 30 of the International Civil Aviation Organization's engine emissions databank. An artificial neural network was created after data cleaning and preparation for its strength in modeling intricate, nonlinear interactions between inputs and predicted emissions. The model generates estimates of the emission index for carbon dioxide, nitrogen oxides, carbon monoxide, and fuel flow. These predictions help assess how adjustments in operational parameters influence emissions. Additionally, the model can support more refined analysis across different flight scenarios by incorporating data from the Automatic Dependent Surveillance–Broadcast and weather information.

1. INTRODUCTION

The aviation sector has a direct effect on the Global Greenhouse Gas (GHG) output. Recent studies indicate that commercial flights are responsible for around 2.5% of the world's carbon dioxide (CO_2) emissions [1]. As air travel continues to expand, the urgency to minimize its ecological effects grows more pressing. Among the range of proposed solutions, the use of Sustainable Aviation Fuel (SAF) stands out due to its renewable origins and its capacity to offer a cleaner alternative to traditional jet fuels. Despite its promise, the large-scale integration of SAF into the industry demands reliable, data-centred approaches capable of accurately estimating its impact, particularly regarding emission reductions.

Various interacting factors, including the technical performance of engines, flight operating conditions, and the characteristics of the fuel, influence aircraft emissions. The dynamic relationship among these elements makes precise emissions forecasting challenging when using conventional approaches [2]. Aviation engines emit different types of air pollutants, including carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM), unburned hydrocarbons (UHCs), and water vapour, with carbon dioxide (CO_2) remaining the most significant contributor to global warming. While CO_2 output directly reflects fuel usage, emissions like NO_x and PM depend on the fuel's chemical makeup and the engine's design [3]. Conventional estimation techniques often rely on oversimplified assumptions or generalized models of fuel burn, which can result in misleading assessments and limitations, especially when analyzing the environmental advantages offered by SAF [4, 5]. In addressing these limitations, machine learning (ML) methods have shown potential as a powerful tool for enhancing the precision of

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emissions forecasting within the aviation industry. Among various ML methods, artificial neural networks (ANNs) are particularly effective due to their ability to model intricate, nonlinear interactions among a wide range of input variables [4]. This makes them especially suitable for analyzing aircraft emissions.

Unlike conventional estimation techniques, ML-based models are capable of processing large, multidimensional datasets encompassing operational conditions such as thrust levels, cruising altitude, and air speed, along with engine-specific parameters and fuel characteristics. When trained on comprehensive data sources, these models can deliver highly accurate predictions and uncover meaningful patterns in how operational and technical factors combine to impact emission outputs. The Engine Emissions Databank (EEDB), maintained by the International Civil Aviation Organization (ICAO), offers a rich dataset containing detailed metrics on engine performance [5]. This resource includes information on engine classifications, thrust levels, and patterns of fuel consumption, making it well-suited for training ML models aimed at forecasting aircraft emissions. When paired with real-time operational data from the ADS-B systems, these models can deliver near-instantaneous estimates of emissions as flights progress [6]. Additionally, by integrating fuel-specific characteristics such as chemical structure, energy content, and combustion behaviour, ML approaches can accurately reflect variations in emissions produced by SAF compared to traditional jet fuels.

This study introduces a machine learning-based model designed to predict aircraft emissions. The model integrates 11 critical input variables, encompassing engine performance data, operational factors, and fuel characteristics. Utilizing version 30 of the ICAO EEDB, the model strives to deliver accurate emissions forecasts. Compared to traditional approaches, this method provides distinct advantages by capturing the intricate relationships between engine operation, flight parameters, and fuel composition. Moreover, it offers valuable insights into the potential emissions reductions achievable through the use of fuel with various aromatic content under several engine configurations and flight scenarios.

2. LITERATURE REVIEW

Amid growing global awareness of climate change and environmental sustainability, the aviation industry is placing greater emphasis on minimizing its ecological impact. This shift in priorities has highlighted the urgent need for more advanced, intelligent systems that can reliably analyze and predict engine emissions under a wide range of flight and weather conditions [7]. Compared to conventional modeling approaches that served as a reliable benchmark, today's aviation landscape is far more complex. The rapid evolution of engine technologies and the rising adoption of SAF have rendered many traditional methods outdated or inadequate. These emerging factors introduce levels of variability and sophistication that older tools were not designed to handle. As a result, there is now a critical push to develop innovative solutions that can keep pace with modern advancements while supporting the industry's broader commitment to reducing greenhouse gas emissions and meeting international sustainability targets [8].

As an example of using ML for estimating aviation emissions, in 2024, a team of engineers successfully developed a model to estimate the actual take-off weight based on ADS-B data with an accuracy of less than 2%, which constitutes an important input for models estimating emissions and fuel flow [9]. Another study exploited ML for calculating NO_x, PM emissions, and fuel efficiency metrics, which used highly accurate multi-layer perceptron (MLP) neural network models to predict emissions and the combustion process properties. The investigation is carried out on a medium-duty diesel engine based on a high-resolution dataset of 6,277 samples as a training source [10]. The aviation industry is also seeking to focus on the emissions effect, not only for commercial aircraft but also for advanced small or personal aircraft [11].

These developments highlight the real capacity of machine learning to improve the precision of accurate emission prediction. As the aviation industry strives toward greener operations, integrating intelligent, data-driven approaches will be key to achieving meaningful and measurable progress in environmental performance.

3. APPROACH AND ML MODEL DEVELOPMENT

The modeling approach adopted in this study is centred on a supervised learning framework using ANNs. The ANN model was selected for its proven ability to handle complex, nonlinear functions within high-dimensional datasets. The methodology integrates multiple sources of information, ranging from standardized engine specifications to real-world flight operations and detailed fuel characteristics, to construct a reliable emissions prediction tool. This combination enables the model to simulate emissions performance under a wide array of scenarios. The development pipeline includes structured phases: data collection, refinement, input selection, model configuration, training, and validation. Each stage is outlined in the sections that follow.

3.1. Data Sources

The core dataset utilized in this research is derived from version 30 of the EEDB, maintained by the ICAO [5]. This dataset contains 834 samples providing standardized emissions and performance metrics for an extensive spectrum of certified aircraft engines, making it a reliable foundation for emissions modeling. Key variables include engine classification, rated thrust levels, and emissions indices for major pollutants, namely NO_x and CO, and fuel flow (FF), recorded under four engine thrust levels: 7% at idle, 30% at approach, 85% at climb-out, and finally at 100% at take-off. This database can be used for aircraft altitude below 914.4 m [3].

3.2. Data Preprocessing

Before training the predictive model, the raw dataset was cleaned comprehensively, filtered, and transformed to ensure data quality and consistency. This included the identification and removal of missing values, as well as the detection and treatment of outliers that could distort model performance.

Additionally, several ambient condition variables were simplified to streamline the dataset and reduce dimensionality without losing critical environmental context. The original dataset included minimum and maximum values for ambient pressure, temperature, and humidity. These were consolidated into three averaged values to reduce redundancy and maintain a manageable number of input features: ambient pressure (kPa), ambient temperature (K), and humidity (kg/kg). Each new variable was calculated as the arithmetic mean of its corresponding minimum and maximum readings. This approach provided a balanced representation of ambient conditions while minimizing potential multicollinearity and simplifying the learning task for the neural network.

As part of the data preparation process, special attention was given to how engine thrust levels were represented. In the original dataset, emissions data were provided across four discrete thrust settings: 7%, 30%, 85%, and 100%. Rather than treating these as separate observations in fixed columns, the dataset was reformatted to better align with the ML model's structure by duplicating the dataset four times, with each duplicate representing one of the thrust levels. A new column labeled "Thrust Level (%)" was introduced and assigned the corresponding value (7, 30, 85, or 100) in each copy. This transformation allowed the thrust level to be treated as a continuous input variable, enabling the model to learn its effect on emissions more flexibly and accurately. Integrating this parameter as a standalone feature enhanced the model's versatility, allowing it to be applied across a broader range of operational conditions, rather than being limited to predefined power settings.

Finally, categorical data were appropriately encoded to ensure compatibility with the ML model. Specifically, Scikit-learn's Label Encoder function was applied to the string input variables to convert their categorical values into a numerical format, enabling the ANN to process them effectively during training [12].

3.3. Model Structure

The architecture of the predictive model is based on a feedforward ANN owing to its proven ability to capture nonlinear interactions between multiple independent variables and continuous emission outputs. As illustrated in Fig. 1, the model is divided into three main parts: the input layer, hidden layers, and output layer. The implementation uses Python scikit-learn's MLPRegressor, which provides a flexible and efficient framework for training and tuning multi-layer perceptron models for regression tasks [13].

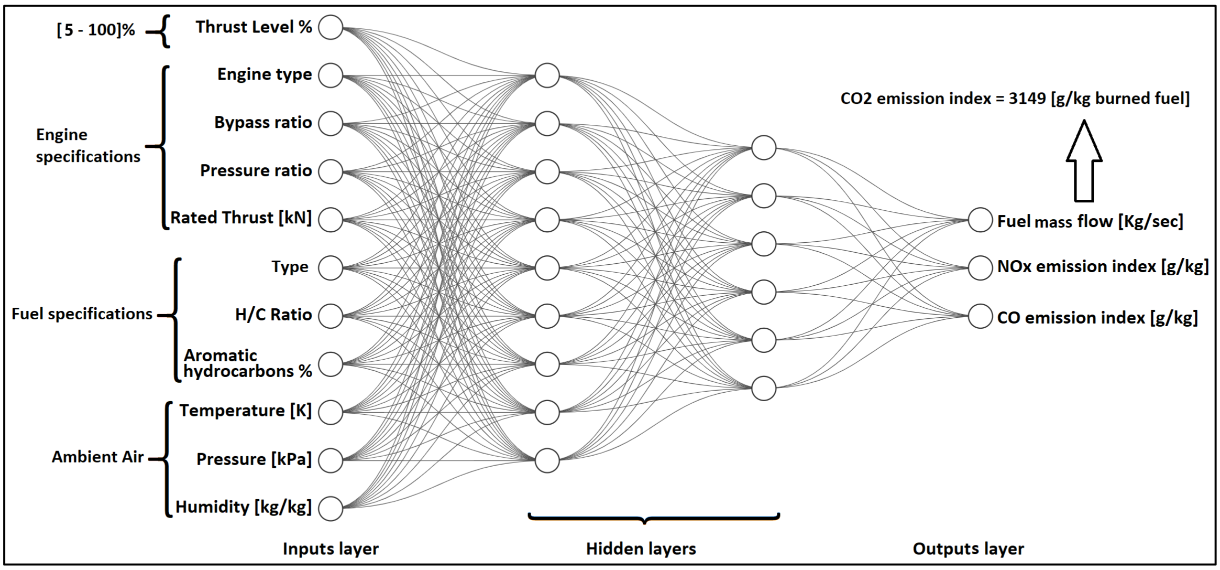

Fig. 1. ANN-model structure for predicting aircraft engine NO_x, CO emissions, and FF

The input layer consists of 11 neurons, each corresponding to a distinct input feature categorized into three groups, as described in Table 1. This includes a diverse set of variables that allows the model to account for the wide range of factors influencing aircraft emissions.

Table 1

The model inputs

Group	Parameter	Unit
Engine specifications	Thrust level %	%
	Engine type	-
	Pressure ratio	-
	Bypass ratio	-
	Rated thrust	kN
Fuel properties	Fuel type	-
	Hydrogen-to-Carbon (H/C) ratio	-
	Aromatic hydrocarbon content	%
Ambient air parameters	Temperature	Kelvin
	Pressure	kPa
	Humidity	kg water/kg dry air

Information flows from the input layer into the hidden layers, where nonlinear transformations are applied. These layers use the rectified linear unit (ReLU) as the activation function [13]. The ReLU function enables the model to learn complex patterns without introducing vanishing gradient issues. The output layer includes three neurons corresponding to the target outputs: fuel flow (in kg/sec), NO_x emission index (in g/kg), and CO emission index (in g/kg). CO_2 emissions can be calculated from the predicted FF using a factor of 3.149 kg CO_2 per kg of burned fuel [3].

Training was conducted using the Adam optimizer, which integrated the benefits of momentum and adaptive learning rates, ensuring faster convergence and stable updates. The mean squared error (MSE) served as the loss function, aligning with the performance metrics to ensure consistency. Furthermore, methods such as early stopping and dropout were employed to mitigate the risk of overfitting and enhance the model's ability to generalize to novel data.

3.4. Model Evaluation

The dataset was divided into two subsets to assess the model's ability to generalize to new, unseen data based on [14]. Specifically, 90% of the data was used for training, allowing the model to learn from a broad range of operational scenarios and engine characteristics, while the remaining 10% was reserved for testing, providing an independent validation set. This method ensured that the model's predictive capability was evaluated on data it had not encountered during training, offering a more realistic estimate of its applicability in real-world settings. A comprehensive assessment strategy was adopted to evaluate the model's predictive performance, focusing on both accuracy and reliability. Four key statistical metrics were used: mean absolute error (MAE), MSE, root mean squared error (RMSE), and R^2 score (coefficient of determination), all of which were calculated using the sklearn.metrics library [15]. Each metric provided unique insights into the model's performance, helping to identify its strengths and areas for improvement. Together, these metrics offered a well-rounded evaluation of the model's ability to capture underlying patterns in the data and its robustness across different emissions scenarios.

MAE measures the average magnitude of prediction errors without considering their direction and provides a straightforward interpretation of how far, on average, the model's predictions deviate from the actual values [16]. MAE is particularly useful because it is not overly sensitive to outliers, making it a reliable indicator of general prediction accuracy across typical operating conditions. Mathematically, MAE is expressed as shown in Equation (1):

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

where:
n: number of data points,
y_i: actual value (ground truth),
$\hat{y}_i$: predicted value for each data point.

MSE quantifies the average of the squared differences between predicted and actual values. By squaring the errors, MSE places greater emphasis on larger deviations, thereby penalizing significant mispredictions more than smaller ones [17]. This makes it especially effective for identifying whether the model occasionally produces substantial errors under specific input conditions. Mathematically, MSE is expressed as Equation (2):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2. \tag{2}$$

RMSE is derived from the square root of MSE and provides an error measure in the same units as the target variable [18]. This makes RMSE more interpretable in practical terms compared to MSE. As expressed formally in Equation (3):

$$RMSE = \sqrt{MSE}. \tag{3}$$

The R^2 score, also known as the coefficient of determination, assesses the model's ability to accurately predict values by measuring the proportion of variance explained [19]. This metric is particularly valuable for assessing the model's ability to generalize across different datasets and operational scenarios. R^2 score is expressed in Equation (4):

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}\ , \tag{4}$$

where:
SS_{res}: sum of squares residuals,
SS_{tot}: total sum of squares.

Three statistical evaluation metrics (fuel flow, NO_x, and CO) were computed individually for each target output so the predictive performance of the machine learning model could be thoroughly assessed. Rather than presenting a single aggregate performance score, separating the analysis across all three outputs revealed subtle differences in prediction accuracy and highlighted areas where the model excelled or underperformed, as shown in Table 2.

Table 2
Performance metrics for the ANN prediction model for fuel flow, NO_x, and CO

Output	MAE	MSE	RMSE	R^2 Score
Fuel Flow	0.028	0.002	0.039	0.998
NO_x	0.423	0.653	0.808	0.995
CO	0.803	4.671	2.161	0.970

In addition to the quantitative summary, visual analysis was conducted through the generation of scatter plots that depict the relationship between actual and predicted values for each of the output variables. Three separate plots were created for FF, NO_x, and CO to illustrate the model's ability to approximate real-world measurements (Figs. 2–4). These figures serve as diagnostic tools, allowing for immediate visual assessment of model fidelity. Ideally, a well-performing model will yield points that cluster tightly along the reference line (x = y), indicating high correlation between predictions and actual values. The extent and nature of any systematic errors or biases in the model's outputs are shown as the deviation from this line. When viewed alongside statistical metrics, these visualizations provide a more complete picture of model effectiveness, offering both numerical precision and visual context.

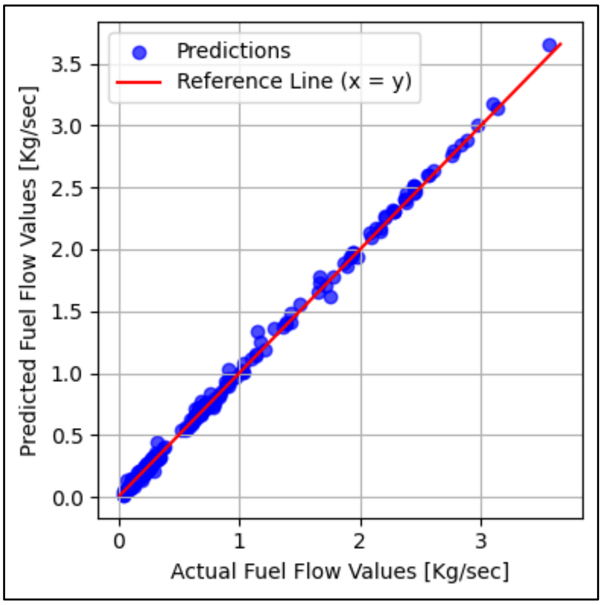

Fig. 2. Scatter plot for fuel flow predicted values vs actual values

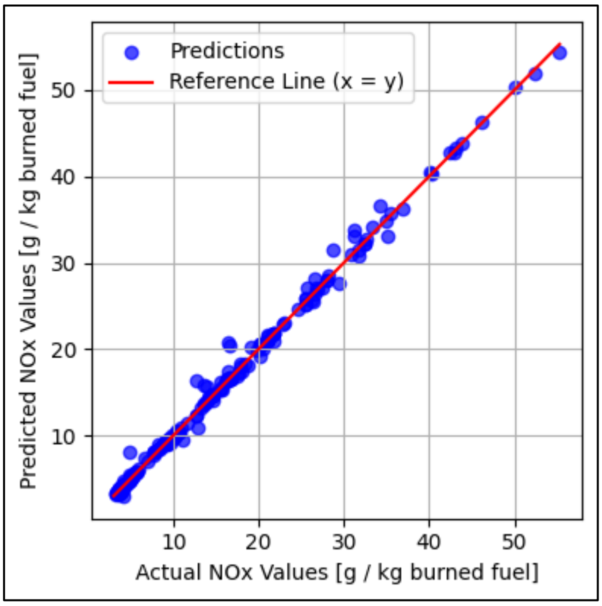

Fig. 3. Scatter plot for NO_x predicted values vs actual values

4. RESULTS

For better evaluation of the ML model, predicted values for fuel flow and emission indexes were compared against reference data [20] from 5% to 100% thrust range of the CFM56-7B26 engine under the same conditions. As shown in Fig. 5, the model demonstrates strong agreement with the reference curves, especially for fuel flow, for which the predictions (solid red) closely match the actual values (dashed red), validating the model's accuracy in capturing core engine behaviour.

The NO_x emission index (solid blue) shows a consistent upward trend with increasing thrust, aligning with expected thermodynamic behavior due to higher combustion temperatures at elevated power settings. This indicates the model's ability to reflect the environmental impact during high-thrust operations like take-off and climb.

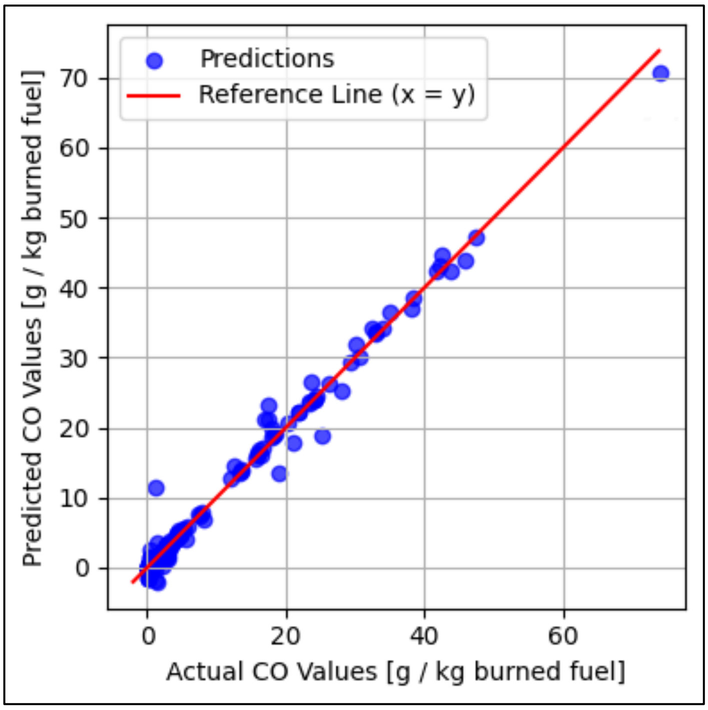

Fig. 4. Scatter plot for CO predicted values vs. actual values

In contrast, the CO emission index (solid green) is highest at low thrust levels and rapidly declines as thrust increases. This inverse trend shows that incomplete combustion at idle and improved efficiency at cruise are captured well by the model.

Overall, the model effectively captures nonlinear interactions between engine inputs and emission behaviour, providing a credible tool for emissions assessment and engine performance.

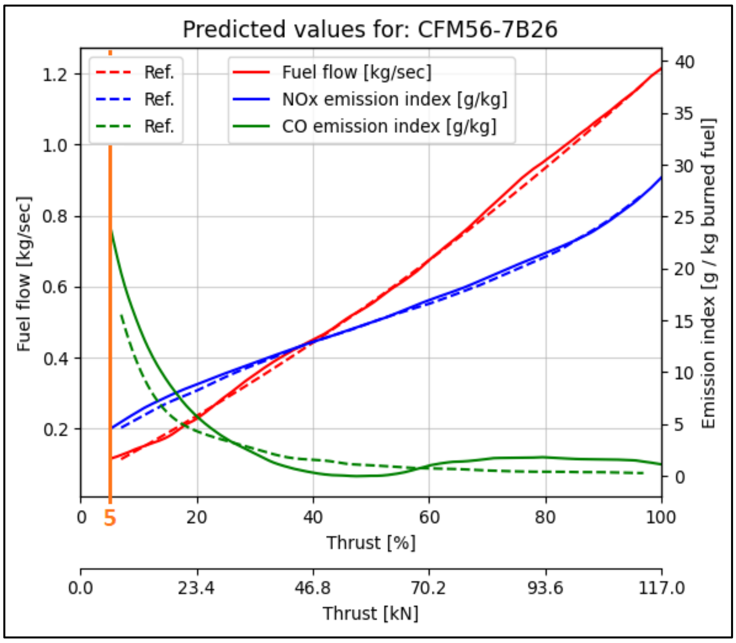

Fig. 5. Predicted values for CFM56-7B26

Another chart was created for the V2500-A1 engine. The model's predictions for fuel flow (red), NO_x emissions (blue), and CO emissions (green) provide insights into combustion behaviour under varying operational loads. As illustrated in Fig. 6 at 100% thrust (for one engine), which represents maximum power during take-off, the model predicts the highest fuel flow, approximately 1.1 kg/sec, consistent with the OpenAP fuel flow calculation model (for two engines) at altitude 0 [21] as shown in Fig. 7.

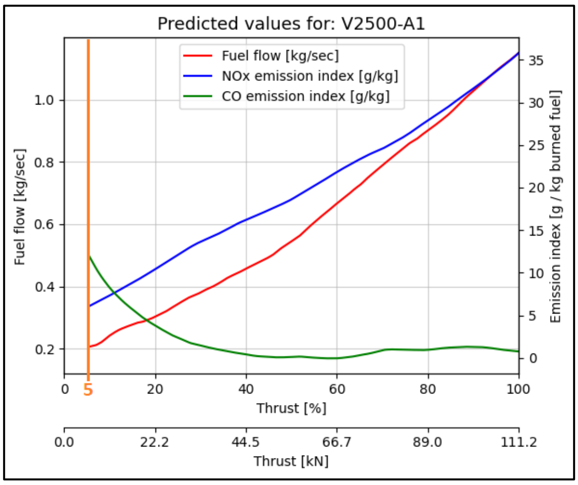

Fig. 6. Predicted values for V2500-A1

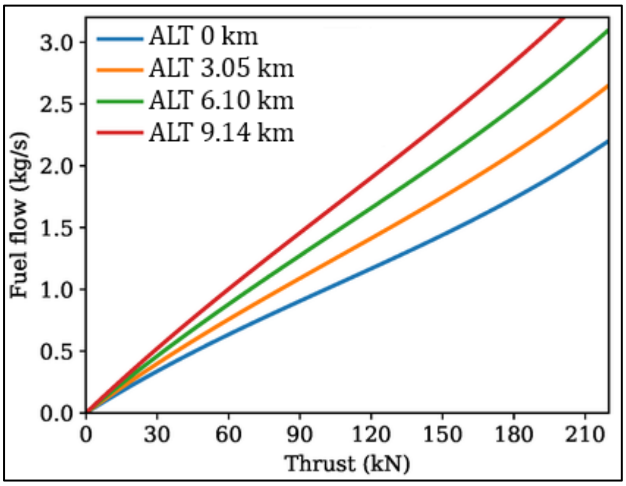

Fig. 6. A320 (V2500-A1 engine) Fuel flow [21]

5. FUTURE WORKS

Future research could build on the current findings by exploring the expansion of emission prediction models to include additional pollutants such as UHC and PM, which are critical for assessing the full environmental impact of aircraft engines. One promising direction is to study the utilization of the ICAO EEDB as a training source, given its standardized structure and extensive coverage of certified engine emissions data. Moreover, future efforts should consider narrowing the modeling focus to a single engine type or family. This approach would reduce the variability introduced by different engine architectures, allowing for more precise tuning of model parameters.

Finally, integrating temporal and environmental variables (such as engine age, maintenance cycles, ADS-B data, and real-time ambient conditions) could further enhance the model's ability to reflect real-world performance. These improvements would support more robust, engine-specific emissions forecasting tools capable of informing policy, optimizing operations, and supporting compliance with increasingly stringent international environmental regulations.

6. CONCLUSIONS

This study introduced a novel ML model designed to predict aircraft emissions by integrating engine specifications, operational parameters, and fuel properties. The model demonstrated a high accuracy rate in estimating key emission indices as evidenced by high R^2 scores for NO_x (0.995), CO (0.970), and FF (0.998). The model provides a novel approach by treating thrust level as a continuous input feature, enhancing the ANN's ability to learn its nuanced effects across the full range of engine operations.

From a theoretical standpoint, this work advances the application of ML in aviation by showing that complex, nonlinear relationships between inputs and emissions can be effectively captured and generalized. The conversion of discrete emissions data into a unified, structured learning format, combined with the consolidation of ambient variables, enabled the ANN to outperform traditional estimation methods in both flexibility and precision.

Importantly, the model's structure allows for the seamless integration of high-resolution, real-time data (e.g., from ADS-B or environmental sensors), enabling dynamic in situ emission estimations. This capability positions the model as a scalable tool for future deployment in operational decision-making, sustainability assessments, and regulatory compliance frameworks, especially as the aviation sector increases its reliance on SAF and seeks more accurate environmental monitoring systems.

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Received 19.05.2024; accepted in revised form 20.08.2025