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Aging Aircraft and Emissions: Machine Learning Predictions in Takeoff and Landing Operations

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Abstract: The aviation industry plays a crucial role in global connectivity and transportation; however, its environmental footprint continues to grow alongside the expanding popularity of aviation. By analyzing a decade-long dataset, the novelty of this research lies in delving into the relationship between aircraft age and major aviation emissions, such as hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NOx), during landing and take-off (LTO) operation using advanced machine learning algorithms. The analysis of this research comprises three horizons. Firstly, an inventory of aircraft emissions was constructed by analyzing aircraft fleet data at Queen Alia International Airport (QAIA) in Jordan. Secondly, the correlation between these emissions and aircraft age was rigorously examined. Finally, predictive models for aircraft age based on pollutant emission features using advanced machine learning algorithms were developed. The findings of the study revealed a discernible impact of aircraft age on emissions, underscoring the importance of considering the aging factor in assessing the environmental implications of aviation. The machine learning models exhibited a capacity to forecast pollutant emissions with a notable degree of accuracy with a Mean Squared Error (MSE) of about 3.0931. This offers valuable perspectives that can enhance comprehension of aviation's environmental footprint.

Key Words	Emissions; Aircraft; Machine Learning; Pollutant; Airport; Age; LTO
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1. INTRODUCTION

The aviation industry plays a pivotal role in global connectivity and transportation, yet its environmental footprint is a subject of increasing concern (Quadros et al., 2020). As aviation continues to burgeon, it becomes imperative to comprehensively grasp the implications of aircraft emissions on environmental issues, such as global warming, and the well-being of affected communities. The impact of aircraft emissions on air quality near airports is an acute concern, with potential ramifications for public health. Numerous studies have established a correlation between elevated levels of pollutants near airports and adverse health effects among nearby residents. For example, fine particulate matter, nitrogen oxides, and other pollutants released during aircraft operations can contribute to respiratory issues, cardiovascular problems, and other health concerns (Bendtsen et al., 2021; Jonsdottir et al., 2019; Manisalidis et al., 2020).

Aircraft engine NOx emissions are mostly produced during takeoff at high temperatures and pressures in the combustor (Bo et al., 2019; Mahashabde et al., 2011). These emissions have been linked to negative health effects, including heightened allergy responses, compromised immune system, and respiratory systems (Arter et al., 2022). Surface NOx reacts with hydrocarbons (HC), carbon monoxide (CO), and volatile organic compounds (VOCs) in the presence of heat and sunlight to produce ozone at ground level (Mahashabde et al., 2011). This low altitude ground level ozone is a secondary pollutant and a major contributor to smog. Exposure to smog can cause respiratory problems, damage to crops, ecosystems, and several health issues (Brunton et al., 2021; Jonsdottir et al., 2019; Mahashabde et al., 2011; Yim et al., 2015). Furthermore, NOx serves as a building blocks for additional oxidized nitrogen compounds, which aid in the production of secondary particulate matter. As a result, NOx influences the ecosystem and air quality both directly and indirectly.

Another pollutant from aircraft operation is hydrocarbons (HC). Elevated concentrations of hydrocarbons, often originating from anthropogenic sources such as vehicle emissions, industrial activities, and fuel combustion, can contribute to air pollution. In urban areas, high concentrations of hydrocarbons are associated with smog formation and diminished air quality, posing health risks to human populations (Mahashabde et al., 2011). Monitoring and controlling harmful emissions concentrations are essential for mitigating environmental pollution and promoting sustainable practices to minimize adverse effects on both human health and the ecosystem.

As aircraft age, the confluence of changing engine efficiency, evolving technology, and varied maintenance practices may significantly alter the release of pollutants (Behere et al., 2020; Lee, 2010). The ageing of the engine is believed to be a major factor that impacts emissions. As engine components, particularly the compressor and turbine, deteriorate, the fuel flow needs to increase in order to achieve the desired power settings. This, in turn, influences the emissions. It is estimated that engine ageing lead to an increase in fuel consumption of about 4–10% (Patterson et al., 2009; Xu et al., 2020). Only a few studies attempted to correlate aircraft age and emissions. For example, Xu et al., (2020) attempted to explore the effect of engine aging on NOx emissions in taxi mode. They concluded that there is no significant correlation between aircraft age and emissions. On the contrary, (Zaporozhets and Synylo, 2017) investigated the effect of engine age on emission indices for CO and NOx. Their results have demonstrated the dependences of the emission indices on engine age. As there is limited literature investigating the ageing of aircraft in the context of environmental sustainability in aviation. This study seeks to investigate the complex relationships between aircraft aging and environmental impact, specifically focusing on aviation emissions.

Leveraging machine learning techniques assumes paramount importance in tackling the complexity inherent in this study problem. Machine learning algorithms possess the capability to sift through vast datasets, identifying nuanced patterns and relationships that might elude traditional analytical methods. In addition, traditional methods can be limited in their ability to capture the intricate non-linear relationships between emissions and aircraft age, potentially leading to inaccurate predictions. Machine learning algorithms surpass at identifying complex patterns and non-linear relationships within data, making them well-suited for the challenging task of predicting aircraft age from emission data. Machine learning involves the exploration of computer algorithms to enable accurate predictions and intelligent responses in specific situations. Fundamentally, it revolves around learning to improve future circumstances based on past knowledge. Machines acquire insights from existing information and experiences, leading to the development of programs that analyze data from diverse sources. These programs select pertinent data and leverage it to predict system behavior in similar or dissimilar scenarios. Machine learning also involves the classification of objects and activities to facilitate decision-making in new input scenarios. The underlying motivation for machine learning lies in the necessity for additional intelligence and learning to address uncertainties (Kulkarni, 2012).

Moreover, supervised learning primarily seeks to establish a model that captures the relationship between inputs and their associated outputs within the provided training data. The objective is to enable the prediction of output responses for new data inputs, leveraging the acquired knowledge of the established relationships and mappings between inputs and their target outputs. Supervised training methods fall into two main categories, namely classification, and regression, depending on the nature of the machine learning problems being addressed (Rathnayake et al., 2024; Sarkar et al., 2018).

Machine learning has made substantial inroads into the field of aviation research. It has been employed in a multitude of applications. For instance, machine learning models can predict climate change due to CO_2 emissions (Askr et el., 2023;Maruhashi et al., 2022). Kayaalp et al., (2021) utilized the Long-Short Term Memory (LSTM) to predict emissions. Furthermore, Aygun et al., (2023) predicted the emissions indices for NOx and CO and fuel flow during take-off and climb-out phases using a hybrid model combining a convolutional neural network (CNN) and LSTM (CNN-LSTM). Wan et al., (2022) predicted emissions and noise impact on air quality. Dursun et al., (2022) focused on predicting various emission indexes (EIs) including CO, HC, and NOx, as well as fuel flow for various commercial aircraft engines during the take-off phase. Two distinct approaches, support vector regression (SVR) and LSTM, were employed for this purpose. Han et al., (2022) utilized machine learning predictive models to investigate the influence of emissions from a civilian airport on the local air quality of nitrogen dioxide (NO_2). Tian et al., (2019) introduced a framework that categorizes air quality in airports by various supervised learning methods. In addition, machine learning applications in aerodynamics optimization enables the development of more fuel-efficient, stable, and easily controllable aircraft. By training machine learning models on data collected from wind tunnel tests, flight tests, and simulations, engineers can accurately predict and optimize design parameters. These optimized parameters are then used to generate 3D models of the aircraft, which are subsequently rigorously tested in a virtual environment to ensure they meet the desired aerodynamic performance standards (Jiang et al., 2023; Le Clainche et al., 2023; Sabater et al., 2022). Artificial intelligence and machine learning have been also integrated to inform and fortify future aviation safety strategies (Demir et al., 2024). Furthermore, machine learning was utilized in optimizing air traffic routes and schedules to reduce congestion and fuel consumption (Kim et al., 2022).

In the context of this research, machine learning serves as a powerful ally in deciphering the multifaceted interplay between aircraft age and environmental impact. As we navigate the intricate landscape of aviation emissions, the role of machine learning becomes increasingly apparent. The algorithms employed in this research enable the prediction of aircraft age based on pollutant emissions, providing a predictive framework that extends beyond mere observation. This proactive approach to understanding the environmental consequences of aging aircraft is instrumental in developing targeted and effective strategies for mitigating these impacts. By harnessing the power of machine learning, the study aspires to not only understand the current impact of aging aircraft on emissions but also to forecast potential trends, facilitating proactive measures for sustainable aviation practices.

The significance of this research addresses critical issues at the intersection of aviation, environmental sustainability, and public health. The novelty of this research comes from the fact that it not only addresses a pressing environmental problem but also its relevance on the local and international scales alike. When examining the literature in detail, any studies on correlating and predicting aircraft age based on emissions using machine learning have not seen to the best of the author's knowledge. Therefore, the present study provides the first attempt to assess the impact of aircraft age on pollutants emissions. Understanding the influence of aircraft age on engine emissions is pivotal for formulating sustainable aviation practices. By identifying the specific environmental implications associated with aging aircraft, this research provides empirical evidence to implement regulations that encourage the adoption of greener technologies and efficient maintenance practices.

The objectives of this study are: (i) develop an inventory of aircraft emissions, including NOx, CO, and HC, during the landing and take-off (LTO) cycle operations in QAIA; (ii) examine rigorously the correlation between the age of aircraft and these emissions utilizing a decade-long dataset; (iii) develop predictive models for aircraft age based on pollutant emissions by employing advanced machine learning algorithms. This will offer insights into the current impact and facilitate the anticipation of potential trends for the implementation of proactive measures.

2. MATERIALS AND METHODS

Study Area

The research area was Queen Alia International Airport (QAIA) in Jordan. QAIA is located about thirty kilometers south of Amman, the capital of Jordan. It has a latitude of 31° 43' 12.59" N and a longitude of 35° 59' 21.59" E (Latitude.to, 2024). It is the largest and busiest airport in Jordan, serving more than 8 million passengers annually. The airport serves as a hub for more than 50 carriers and airlines that connect the country to various destinations in the Middle East, Asia, Africa, and Europe.

Data collection and processing

The required data for developing an inventory of aviation emissions for QAIA were collected. Initially, the fleet data spanning from 2013 to 2022 pertaining to QAIA were obtained from the Jordan Civil Aviation Regulatory Commission and the air transport department. The recorded flight data encompassed details such as aircraft engines, registration, country, types, weight, aircraft movements (ACM), total passengers, and cargo. An examination to ensure the cleanliness, consistency of the data, and detection of any outliers has been carried out. Information about the typical engine combinations on various aircraft types was obtained from the Airfleet Aviation website ("Airfleets aviation," 2023). Engine emission indices were obtained from the ICAO Aircraft Engine Emissions Databank ("ICAO," 2023).

Aircraft emission calculation

Aircraft emissions depend on various factors, including the type and number of aircraft, engine type, fuel, duration of each operation phase, power settings, and flight distance (Yang et al., 2018). Usually, research on aircraft emissions and their effects is typically divided into two categories. The first category is related to aircraft pollutant emissions that occur during the LTO phase, which are referred to as local pollutant emissions. The second category is the non-LTO flight phase that takes place above 915 meters and at cruise level (Bajgai and Shrestha, 2023). The focus of the current study was the aircraft emissions impact on local airport air quality, therefore the emissions of aircraft during the LTO phase were only considered. The LTO cycle comprises four phases: approach, taxi/idle, take-off, and climb. A schematic diagram of the LTO cycle operation is shown in Fig 1. Emissions during a particular phase of the LTO cycle are also proportional to the amount of time spent on each mode, main engine index, and engine fuel flow. In this study time in mode and thrust setting on each operation phase are taken from the ICAO standard LTO cycle (Table 1).

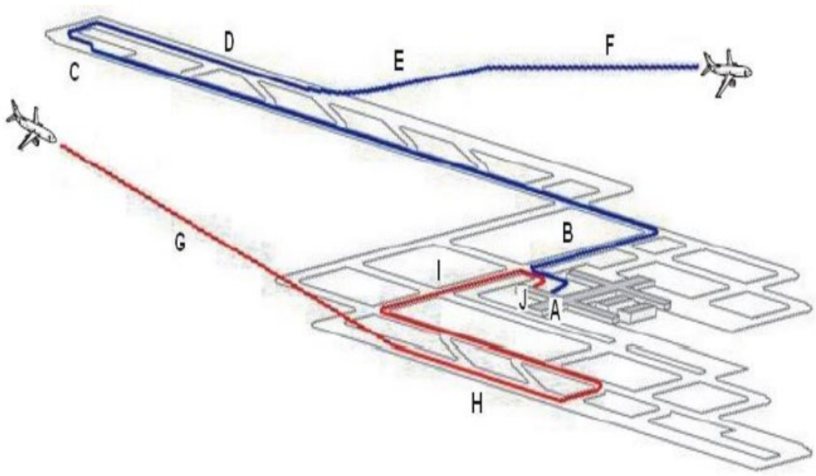

Fig. 1. ICAO Standard Operational flight landing and take-off (LTO) cycle (ICAO,2016)

Table 1. Time in mode and thrust setting on each operating phase during the LTO cycle (ICAO,2016)

Operating phase	Time-in-mode (minutes)	Thrust setting (percentage of rated thrust)
Approach	4.0	30
Taxi /idle	26 7.0 (in) 19.0(out)	7
Take-off	0.7	100
Climb	2.2	85

The emissions for a specific pollutant i of a particular aircraft type j are calculated by the following equation:

$$Ei_j = \sum\left(TIM_{jk} * 60\right) * (FF_{jk}) * (Ei_{ijk}) * (Ne_j) \qquad (1)$$

Where Ei_j= total emissions of pollutant i (e.g. NOx, CO or HC), in grams produced by aircraft type j for one LTO cycle; Ei_{ijk} = emission index for pollutant i, in grams pollutant per kilogram of fuel (g/kg of fuel), in mode k (e.g. take-off, climb-out, idle and approach) for each engine used on aircraft type j; FF_{jk} = fuel flow for mode k, in kilograms per second (kg/s), for each engine used on aircraft type j; TIM_{jk} = time-in-mode for mode k, in minutes, for aircraft type j; Ne_j = the number of engines used on aircraft type j.

Machine Learning and Artificial Neural Network

An artificial neural network (ANN) is a model inspired by the human brain's structure and functioning, with nodes and interconnections resembling neurons. In a standard ANN, there are typically input and output layers, with at least one hidden layer in between as shown in Fig 2. The network comprises specific link patterns, layer connections, connection weights, and neuron activation functions mapping inputs to outputs. During training, weights are adjusted using the backpropagation algorithm, involving propagation and weight update stages. Input data sample vectors are forwarded through the neural network to generate output values. The produced output vector is compared with the desired output vector. Performance is evaluated using mean square error (MSE) that measures the average squared difference between the actual values (Y_i) and the predicted values ($\widehat{Y_i}$) generated by a model and is computed according to the following equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \qquad (2)$$

The node weights can then be adjusted based on corrections that minimize the error in the entire output for the nth data point, given by the following equations:

$$\varepsilon(n) = \frac{1}{2}\sum_{output\ node\ j} e_j^2\,(n). \tag{3}$$

Using gradient descent, the change in each weight $\Delta w_{ji}(n)$ is

$$\Delta w_{ji}(n) = -\eta \frac{\partial \varepsilon(n)}{\partial v_j(n)} y_i(n) \tag{4}$$

where $y_i(n)$ is the output of the previous neuron i, and η is the learning rate, which is selected to ensure that the weights quickly converge to a response, without oscillations. In the previous expression, $\frac{\partial \varepsilon(n)}{\partial v_j(n)}$ denotes the partial derivate of the error $\varepsilon(n)$ with respect to the weighted sum $v_j(n)$ of the input connections of neuron i.

These stages are repeated through multiple iterations (epochs) until reliable results are obtained. A multi-layer perceptron (MLP) is a fully connected feedforward artificial neural network with at least three layers. Backpropagation can train MLPs and even deep neural networks with multiple layers (Sarkar et al., 2018).

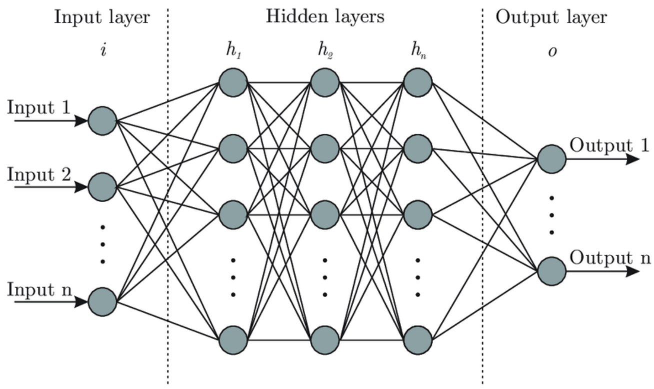

Fig. 2. Architecture of Neural Network

The data has been preprocessed to handle any missing values or outliers. Techniques like imputation and standardization have been employed. Missing values in the dataset were addressed using an imputation strategy. Continuous features were filled using the mean value of the respective feature, ensuring the data's central tendency was preserved. Outliers were identified through visual inspection of plots for each numerical feature and data points that deviated significantly from the general distribution of values were flagged as potential outliers. Consequently, each flagged data point was evaluated in the context of domain knowledge. For instance, unusually high emissions for certain aircraft types were cross-verified against aircraft specifications and operational anomalies. However, outliers deemed to be errors or non-representative of typical conditions were either removed or corrected based on corroborating evidence from the dataset. Finally, after handling outliers, the data distribution was re-evaluated to ensure that adjustments preserved the overall trends and relationships in the dataset. All numerical features were standardized to a mean of 0 and a standard deviation of 1 to ensure that each feature contributed equally to the model training process. These preprocessing steps were implemented systematically using the scikit-learn library, and the codebase ensures reproducibility by following a documented workflow.

The correlation between aircraft age and various emission characteristics has been assessed to identify which emissions exhibit a significant correlation with age. The neural network architecture has been initially configured and fine-tuned based on the specific features that show meaningful correlations with age. The normalized dataset was divided into two datasets 80% training and 20% testing. To measure the model's generalization performance, MSE was applied to the test dataset.

The architecture of the MLPRegressor model, consisting of two hidden layers with 100 and 50 neurons respectively, was chosen after performing hyperparameter tuning experiments. These experiments tested various configurations to balance model complexity and computational efficiency. The first hidden layer with 100 neurons captures complex relationships within the dataset, while the second layer with 50 neurons further refines the feature interactions. This structure ensures that the model effectively handles the nonlinearities inherent in the relationship between emissions and aircraft age. The rectified linear unit (ReLU) was used as the default activation function for Multilayer-Perceptron Regression (MLPRegressor) in scikit-learn. The output layer contains a single variable – predicted age in this case.

3. RESULTS AND DISCUSSIONS

3.1. LTO emission estimation

The LTO emissions in QAIA were analyzed for temporal variations flights from 2013 to 2022. Fig. 3 shows the number of aircraft movements over the investigated period. There was a gradual increase in the number of flights with time between 2013 to 2019. In 2020, there was a significant drop in the number of aircraft movements due to the impact of the COVID-19 pandemic, which resulted in widespread travel restrictions and reduced air travel. There was a partial recovery in the number of flights in 2021 compared to 2020, but it doesn't reach the levels seen in the pre-pandemic years. In 2022, there was a notable increase in the number of flights, possibly indicating a continued recovery of air travel.

The estimated LTO emissions followed a similar trend to the number of aircraft movements as illustrated in Fig. 4. The emissions are generally increasing up to 2019, where peak emissions of 25, 256, and 549 tonnes were recorded for HC, CO, and NOx, respectively. The average LTO emissions of HC, CO, and NOx, were estimated to be around (21. 3 ± 4.8), (207.1 ± 44.9), and (440.6 ± 99.9) tonnes per year respectively. NOx emission has the highest contribution to LTO cycles, followed by CO and HC in QAIA. The significant drop in the three emissions in 2020 is a clear reflection of the impact of the COVID-19 pandemic. This emphasizes the direct relationship between aviation activity and environmental emissions. The recovery in 2021 and 2022, seen in both the number of flights and pollutants releases, may suggest a return to pre-pandemic levels of air travel and associated environmental impact. This recovery trend raises questions about sustainable practices and the need for continued efforts to reduce emissions.

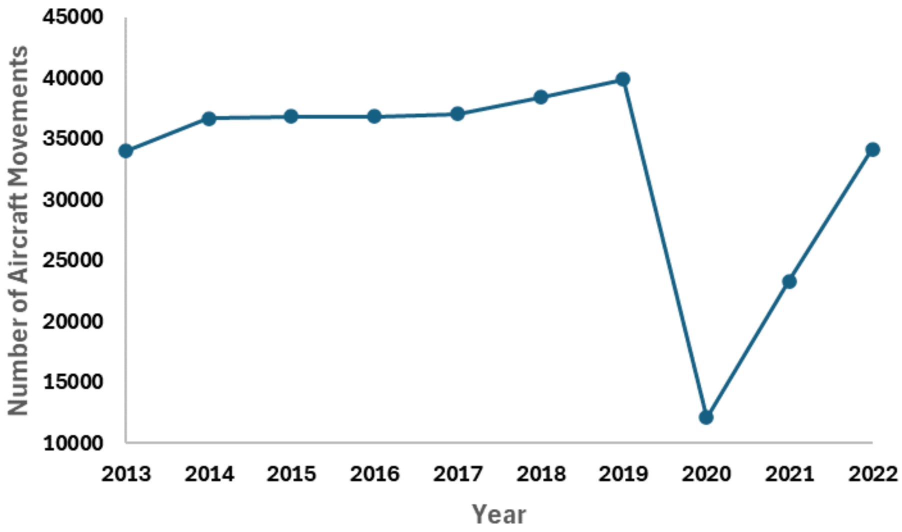

Fig. 3. Total aircraft movements at Queen Alia International Airport (QAIA) from 2013 to 2022

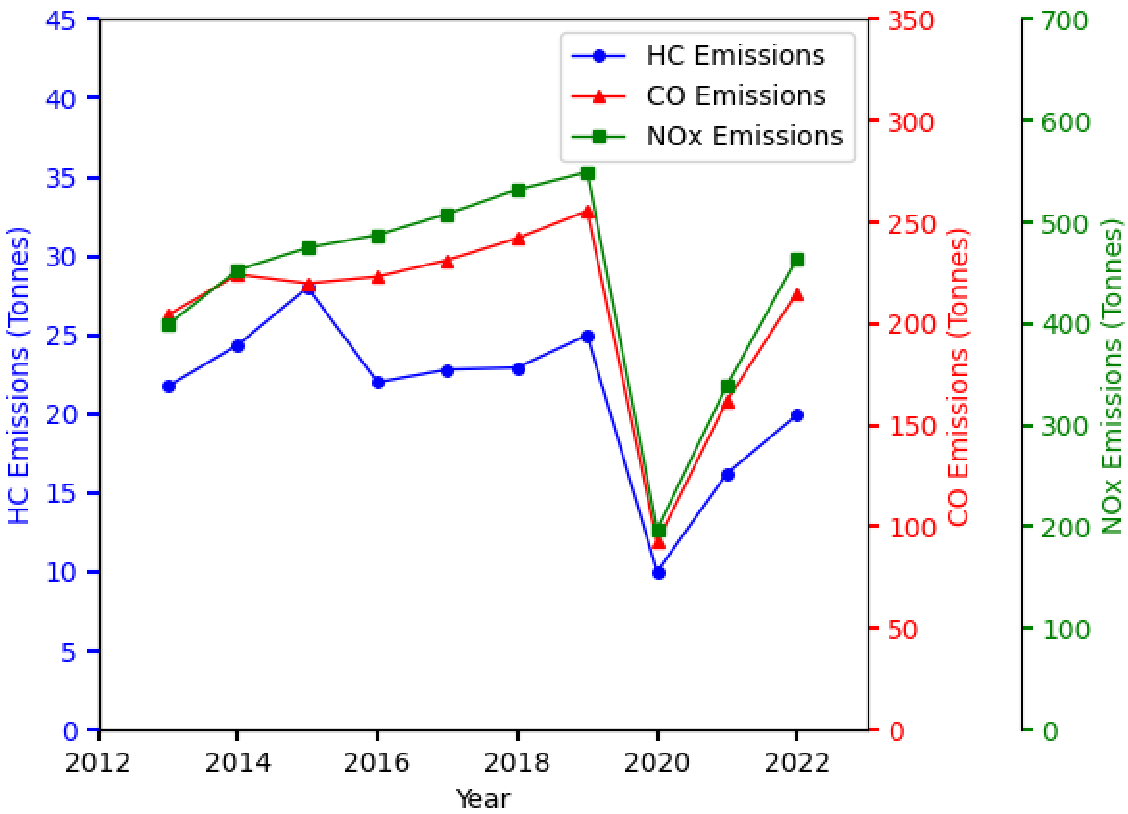

Fig. 4. Estimated total LTO cycle emission in QAIA

3.2. Emissions distribution in different aircraft operation modes

The results revealed that taxi/idle mode has the largest contribution of 35.9% to LTO emissions, while emissions during approach, take-off, and climb phases accounted for 10.8%, 18.5%, and 34.9% of the total emissions, respectively. By analyzing the distribution of each pollutant in different aircraft operation phases of the LTO cycle including take-off, climb, taxi/idle, and approach, it was found that there were significant discrepancies in the emission rates of various pollutants in each mode. Fig. 5 and Fig. 6 show that HC and CO were significantly emitted in the taxi/idle phase, accounting for 92.3% and 91.6% of the total emissions. Similar trend were observed by other researchers (Bajgai and Shrestha, 2023). The emission indices of HC and CO decreased with increasing thrust (Stettler et al., 2011; Yang et al., 2018). So, when the aircraft is on the ground and in taxi/idle mode, it operates at a low power setting where the pressure and temperature are relatively low. This can cause incomplete combustion of fuel and result in increased emissions of CO and HC. The emissions during the taxi/idle phase contribute consistently to the total. Identifying factors influencing emissions during this phase and implementing measures to reduce emissions may have a substantial impact. This can provide insights into changing operational practices, technological advancements, or regulatory influences.

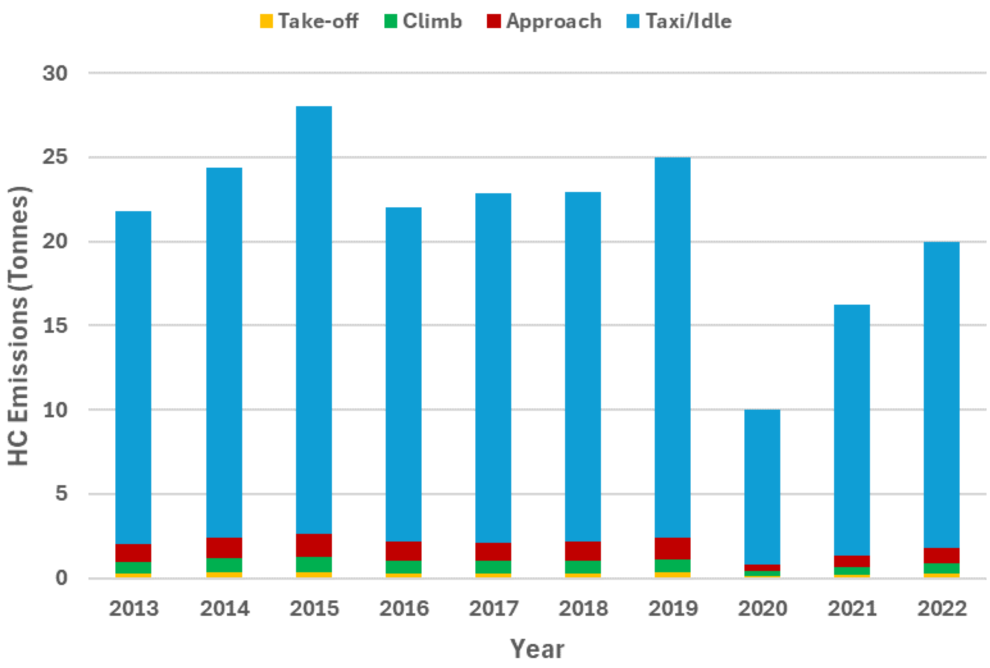

Fig. 5. HC emissions of different LTO operation modes

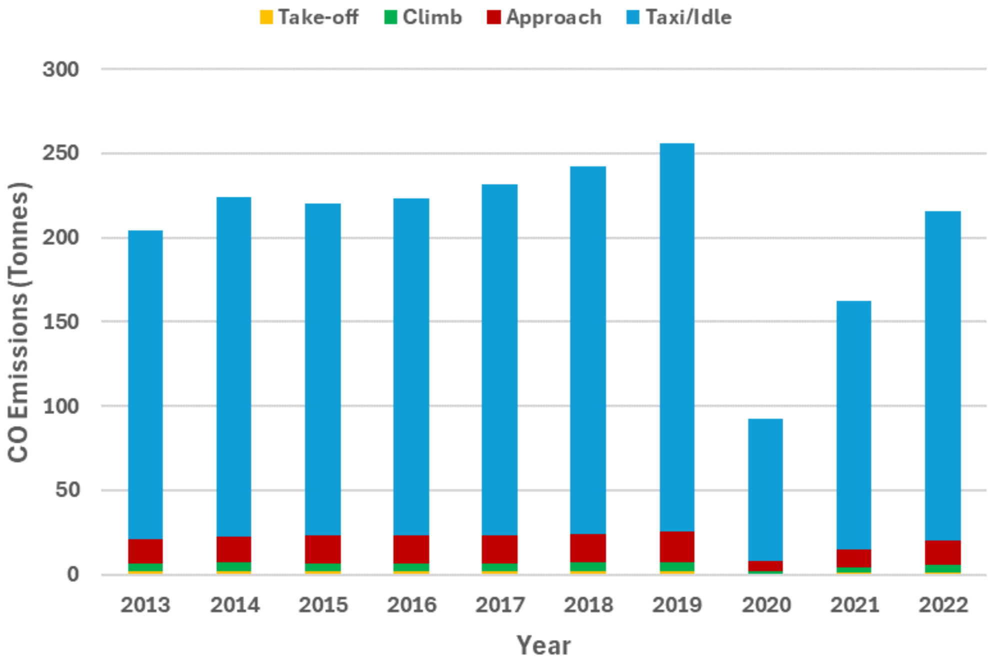

Fig. 6. CO emissions of different LTO operation modes

On the other hand, the highest contribution for NOx was in the climb phase with 51.6 %. While it accounted for 27.6%, 13%, and 7.5 % in take-off, approach, and taxi/idle phases, respectively (Fig. 7). The NOx emissions indices for all aircraft engines are positively correlated to thrust setting. Thus, the highest emission rates of NOx were in the high thrust operation mode of the aircraft during the phases of climb and take-off. Moreover, NOx emissions during take-off show an increasing trend over the years, reaching the highest level in the last few years. This suggests a potential need for optimizing engine performance during the take-off phase. Climb NOx emissions also exhibit a general upward trend, indicating a possible correlation with increased air traffic or changes in flight profiles. Efficient climb-out procedures may be explored to mitigate these emissions. Observing yearly fluctuations in NOx emissions highlights the dynamic nature of aviation emissions. Identifying the reasons behind these fluctuations can aid in implementing targeted measures for emission reduction. Understanding the environmental impact of NOx emissions during different flight phases is crucial for developing strategies to minimize the overall contribution of aviation to air pollution. These strategies include optimizing flight procedures (minimizing ground idling, implementing continuous descent approaches, and optimizing climb profiles), improving infrastructure, encouraging the use of sustainable aviation fuels, investing in research and development of new technologies, and implementing regulatory measures such as emissions trading schemes, performance-based standards, and environmental charges.

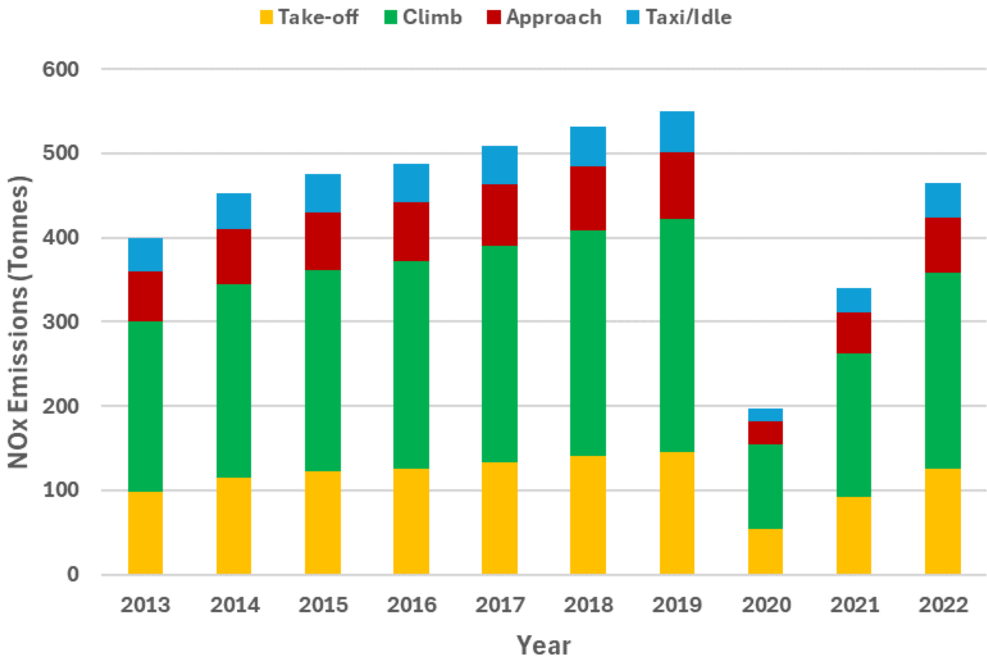

Fig. 7. NO emissions of different LTO operation modes

3.3. Correlation between aircraft age and pollutant emissions

In order to investigate the effect of aircraft age on emissions, the aircraft were grouped in five years old period. Fig. 8 illustrates how emissions of HC, CO, and NOx change across different aircraft age groups. The average HC, CO, and NOx emissions show a notable increase from age 5 to 40, indicating a correlation between age and emissions. The magnitudes of emissions vary significantly between different age groups. Age 40 appears to be a notable peak for all three types of emissions. This may indicate that the engine deteriorates with age besides other factors related to this age group which contribute to higher emissions. Linear fit analysis of each pollutant emissions with aircraft age shows a positive correlation with a coefficient of determination (R^2) equal 0.5183, 0.4767, and 0.6078 for HC, CO, and NOx, respectively. A similar positive correlation was obtained by other researchers when they correlated engine age with emission indices in idle phase only for CO and NOx (Zaporozhets and Synylo, 2017). Conversely, trends where observed by (Xu et al., 2020) who stated that there was no significant correlation was detected between the age of the aircraft and NOx emissions in taxi mode. Also, emissions are influenced by other factors in addition to age, including aircraft type, engine efficiency, maintenance practices, operational methods, among others. These additional elements contribute to the complexity of the study.

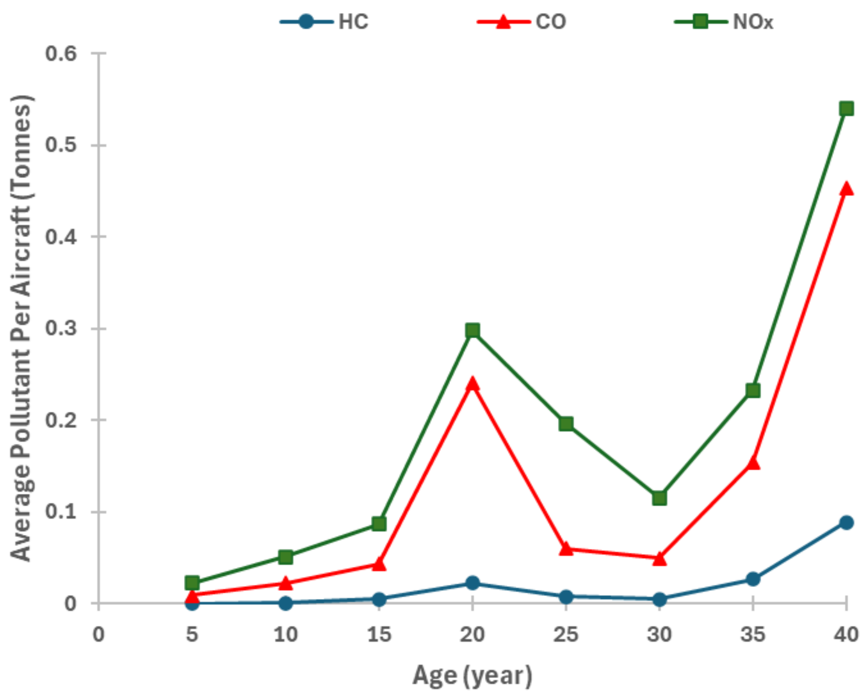

Fig. 8. The 5-year age group with emissions of HC, CO, and NOx

3.4. Machine Learning Predictions for Age

In this section, we embarked on a detailed exploration of a regression task employing the MLPregressor model. The foundation of this analysis lies in a dataset containing pertinent features, with the aim of predicting the variable 'age'. To perform a detailed analysis of the results based on the provided features, correlation coefficients were calculated between the 'age' variable and various features in our dataset as shown in Table 2. These coefficients provide insights into the linear relationships between age and various emissions characteristics. Table 2 shows that the correlation coefficients between age and different features span the range of – 0.30 to about 0.55. This indicates that some variables have a negative inverse relationship, such as NOx EI with a correlation coefficient of – 0.30, and the others have positive, like NOx Dp/Foo Characteristic (which is the mass of NOx emitted during the reference landing and take-off cycle, divided by the rated output of the engine). While some variables have strong linear relationships, others have weak correlations. This gives an insight about this correlation. Positive correlations indicate that as the age of the aircraft increases, the corresponding feature also tends to increase, and vice versa for negative correlations.

Table 2. Correlation coefficients between the 'age' variable and various features in our dataset.

Features	Correlation Coefficient
HC T/O (g) (takeoff), HC C/O (g) (climb out)	0.30
HC App (g) (approach), HC Idle (g), HC TOT (total in g)	0.22
CO T/O (g) takeoff	0.36
CO C/O (g) climb out	0.32
HC Dp/Foo Characteristic (g/kN)	0.16
HC Dp/Foo Characteristic (% of Reg limit)	0.18
HC LTO Total mass (g)	0.22
CO Dp/Foo Characteristic (g/kN)	0.24
CO Dp/Foo Characteristic (% of Reg limit)	0.26
NOx Dp/Foo Characteristic (g/kN)	0.24
NOx Dp/Foo Characteristic (% of original standard)	0.52
NOx Dp/Foo Characteristic (% of CAEP/2 standard)	0.52
NOx Dp/Foo Characteristic (% of CAEP/4 standard)	0.55
NOx Dp/Foo Characteristic (% of CAEP/6 standard)	0.55
NOx Dp/Foo Characteristic (% of CAEP/8 standard)	0.55
NOx EI T/O (g/kg)	-0.17
NOx EI App (g/kg)	**-0.12**
NOx EI Idle (g/kg)	-0.30
NOx TO, NOx APP, NOx TOT, NOx IDLE, NOx LTO Total mass	<-0.01

The predicted age values can be visualized against the actual age values in a scatter plot to realize how well the model is capturing the relationships. Fig. 9 shows a scatter plot where the horizontal axis represents the actual age values, and the vertical axis represents the predicted age values. Points closer to the diagonal line indicate accurate predictions, while deviations from the line suggest errors in the predictions. The findings showed the MSE value of 3.0931. In this case, since the target variable is age, the estimated MSE is considered reasonable based on the specific context and requirements of our study. More details about model performance are shown in the residuals' plot (Fig. 10). It highlights the areas where the model was able to capture the underlying patterns in the data.

The analysis of emissions across different aircraft types revealed a nuanced relationship with age. While there were general trends of increasing emissions with age, the patterns were diverse and specific to each aircraft model. Peaks and drops in emission levels within certain age groups suggest that age was indeed a factor influencing emissions. Evidence indicates that older aircraft generally exhibited higher emissions, aligning with industry expectations. However, this impact was not uniform across all aircraft types, emphasizing the uniqueness of each model. This variable has not been thoroughly examined in this study; further investigation is required.

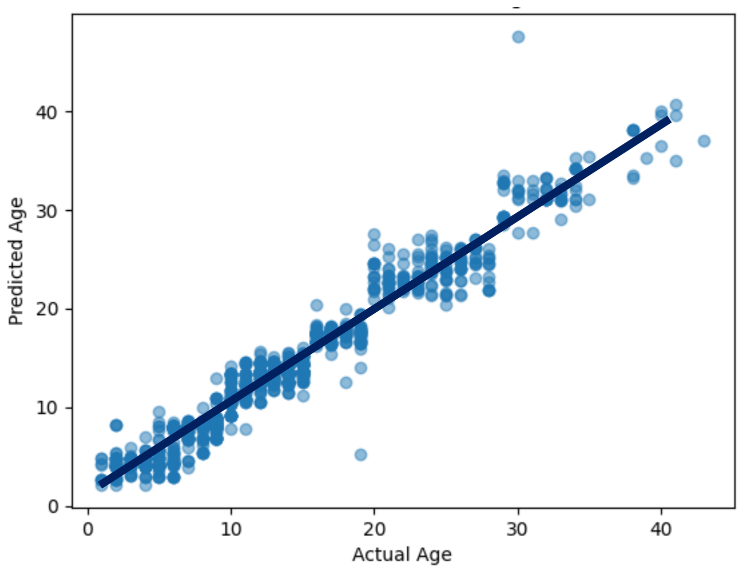

Fig. 9 The predicted age values against the actual age values in a scatter plot

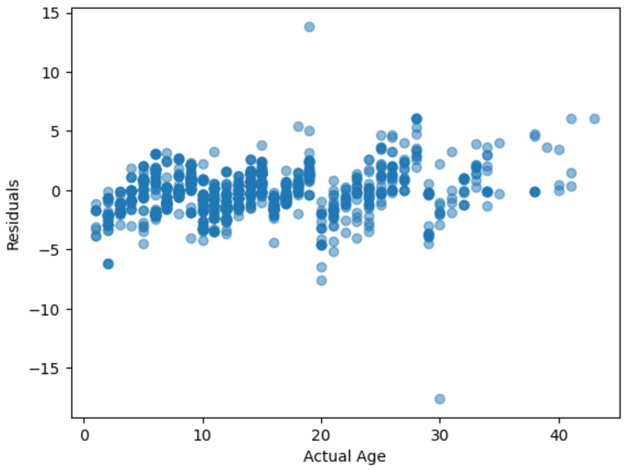

Fig. 10. The residuals plot between the actual and predicted age values.

4. CONCLUSIONS

The rise in aircraft flights and subsequent increase in emissions has raised global concerns. This research is crucial because it addresses vital challenges at the nexus of aviation, environmental sustainability, and public health. This study provided significant contributions at both the local and international scales. Firstly, for the first time, the overall emission of the LTO cycle in QAIA in Jordan was estimated in the period from 2013 to 2022. Secondly, it assessed the relationship between aircraft age and major engine emissions, such as HC, CO and NOx. Such investigations were relatively not covered fully in open literature. Thirdly and most importantly, upon detailed examination of the literature, any studies on correlating aircraft age with emissions features using machine learning have not seen to the best of the authors' knowledge. So, the novelty of this paper is the use of this advanced machine learning tools to uncover the complex relationship between different emission features and aircraft age. As understanding how aircraft age influences engine emissions is crucial for developing sustainable aviation operations, this research makes significant contributions by identifying the specific emission features associated with aging aircraft. This can be translated into actionable insights for the development of targeted strategies aimed at minimizing the aviation environmental footprint. This may include implementing age-based maintenance programs, investing in fuel-efficient aircraft by replacing older aircraft with newer, and more environmentally friendly models, investigating and adopting advanced technologies like biofuels, electric propulsion, and hydrogen-powered aircraft to reduce emissions across their fleet, incentivizing sustainable aviation practices, and promote the use of sustainable ground operations.

Future research activities include expanding the investigation to assess the emissions from other pollutants, such as CO_2 and particulate matter, and to seek applying this methodology to other airports in the region. Finally, challenges encountered in this research include variability in the quality of the available records, some aircraft types have limited number of flights prevent thorough investigation, and difficulties to obtain measured emissions. In addition, a limitation of the used dataset lies in the potential variability of engine types and maintenance practices across the aircraft fleet. Differences in engine models, their age, and maintenance histories can significantly influence emission profiles.

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