Predicting Future Aircraft Emissions in Indonesia: A Comparative Analysis using LSTM and GRU Methods

Filipus Mahendra[1] Reici Ratasya Putri S [2], Sheyla Hannim[3], Mufti Arifin[4]

{Filipus.mahendra@gmail.com[1], reiciratasya14@gmail.com[2], sheylahannim30@gmail.com[3], muftiarifin@gmail.com[4]}

Air Marshal Suryadarma Aerospace University, Jakarta 13610, Indonesia[1,2,3,4]

Abstract. The aviation industry in Indonesia continues to expand resulting in concerns over the environmental impact of aircraft emissions have become paramount. This article presents a comprehensive analysis of future emission predictions using two advanced time series forecasting methods, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), applied to historical aircraft emission data (Q3 2022 to Q3 2023). Leveraging the sequential nature of the data, LSTM and GRU networks are harnessed to model the intricate temporal dependencies and inherent seasonality present in the emission time series. The evaluation encompasses various performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2), to gauge the models' predictive capabilities across different forecasting horizons. Results indicate that both LSTM and GRU methods demonstrate promising forecasting capabilities, outperforming traditional time series models. However, subtle distinctions emerge in their predictive efficiency. LSTM exhibits superior performance in capturing long-term dependencies and handling complex emission patterns, whereas GRU showcases efficiency in shorter forecasting horizons. Remarkably, the research uncovers the profound impact of ML, with the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) methods emerging as the most potent tools with an accuracy reached up to 87%.

Keywords: Aircraft emissions, Long-Short Term Memory (LSTM), Gate Recurrent Unit (GRU).

1 Introduction

Chemicals and many substances are radiatively and chemically active and transported across some areas of the world by the aircraft, which serve as high-altitude emissions vectors. These compounds cause a net global warming effect that accounts for 3.5% of anthropogenic emissions' contribution to climate change. All nations, including Indonesia, are suffering from global warming. The World Meteorological Organization (WMO) reported that 2022 came in at number six on the list of the world's hottest years, and WMO predicted by the end of the year, global warming increased [WMO]. The aviation industry is under pressure to reduce its emissions. This is especially difficult for long-range aircraft, which consume 44% of aviation's kerosene [1]. The average temperature of an aircraft can be used to determine the climate impact [2]. The climatic response of aircraft emissions is affected by the state of the surrounding atmosphere

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[1]. The emissions generated by the combustion of aircraft engines consist of various compounds containing carbon. The Primary emissions from kerosene fuel combustion in most aircraft engines are carbon dioxide, water, and trace molecules such nitrogen oxides (NOx), carbon monoxide (CO), unburned hydrocarbons (HC), and others [1]. Climate change was a serious issue, climate action, included in a series of 17 categories of SDGS (Sustainable Development Program Goals) which is the program initiated by the United Nation. Using a traditional statistical method would be a more challenging way to notice the trends and patterns since the time-series data of the emissions are non-stationary and have complex relationships. Therefore, Machine Learning would be the best tool to evaluate more into the results.

Emission forecasting is a predictive methodology that centers around the utilization of Artificial Neural Networks (ANNs), employing a variety of techniques for resolution. ANNs, as a machine learning approach, emulate the mechanisms of biological neurons. In 1962, a multi-layer perception (MLP) model was proposed which is a neural network with a fully-connected architecture with good performance [3]. Nevertheless, Artificial Neural Networks (ANNs) are not inherently designed for sequential data processing, a common requirement in time-series data. To address this limitation, Recurrent Neural Networks (RNNs) emerge as a suitable choice, offering the capability to anticipate outcomes, with nodes serving as memory cells to retain computations in case of prediction errors. This facilitates efficient backpropagation, enhancing data accuracy. Recurrent Neural Networks (RNN) are able to perform their tasks based on some old information recorded in their memories. They are similar to a network that has a loop in them in order to keep track of old information [4].LSTM have the sufficient ability to solve the problem of long-term dependencies which general RNNs (Vanilla RNNs) cannot learn for the prediction [5]. The Gated Recurrent Unit (GRU), another type of RNN, offers a simpler structure compared to LSTM. This study incorporates foundational techniques such as Autoregressive Integrated Moving Average (ARIMA), Multilayer Perceptron (MLP), and Random Forest (RF). These methodologies will be benchmarked against the LSTM-GRU approach to predict multi-emission levels of aircraft during flight phases Take-off, Climb, Approach, and Landing, potentially yielding significant data-driven refinements. Emission Index and fuel burning data taken from the aircraft type. Flight data obtained from flightradar24 based on 20 to 50 aircraft registrations on airlines in Indonesia. The calculation approach is from September 18, 2022, to September 21, 2023. Fuel combustion and emission index calculations for each type of aircraft engine are obtained from ICAO (International Civil Aviation Organization) Engine Emission Database.

2 Aircraft Engine Emissions

In the previous study, an analysis of Aircraft Gas Emission during Taxi-Out Operation with Single Engine Operation using actual operational data of aircraft at soekarno- Hatta International airport from January to July 2019 for all domestic and international flight with cargo routes. The calculation uses a hybrid approach or a combination of the advanced approach and the sophisticated approach calculations with a single engine taxing strategy for the calculation of aircraft gas emissions for three pollutants(HC,CO,NOx.) The calculation approach of using a single engine can produce a comparative emission and potential aircraft emission reduction for 37% until 40% depending on the type of pollutant. [6].

In the previous study,analysis of the growth of aircraft use against carbon emission loads at juanda international airport using the overall movement of the aircraft, which has been projected through predictive methods using exponential smoothing techniques and linear econometric regression analysis, showing less significant fluctuations and tending to show improvement. The highest emissions come from carbon dioxide (CO_2), in a massive quantities.Based on the analysis, known that the correlation analysis between population growth and forecasting of increased aircraft movements using the SPSS method with an accuracy rate of 90% and an error () of 10%. [7].

Aircraft emission measurement studies were also carried out at Pudong Shanghai International Airport using land-based aircraft operating data from the Aircraft Communication Addressing and Reporting System (ACARS) data set to obtain emission parameters specific to PVG (Shanghai Pudong International Airport) on various combinations of aircraft engines during the taxi inbound and taxi outbound phases in the landing and take-off cycle (LTO). This emission parameter, along with the PVG-specific operating conditions, was then used to measure annual emissions in 2017.The analysis obtained emissions of HC, CO, NO_x, NO, NO_2, HONO, HNO_2, SO_2, BC, and $PM_{2.5}$ emissions from aircraft activity in PVG measured using aircraft performance data. These emissions were found to be the very dominant source of emissions at airports. [8].

3 Approach to Calculating Aircraft Engine Emissions

There are three approaches that can be used to calculate aircraft emissions based on the availability of data and information. The first approach is the simple approach, the second is the advance approach, the third is the sophisticated approach.[9]. Based on research and previously obtained data, the calculation approach to be used is The Advanced Approach data and information used, i.e. aircraft type, engine type, EI calculation and Time in Mode. This approach takes into account local conditions by integrating several aircraft performance calculations. (aircraft performance). The results of the calculation of exhaust gas emissions from aircraft engines using this approach are more accurate than the simple approach. Nevertheless, the total emission calculations are still considered conservative. Each flight produces a huge amount of exhaust gas emissions that can be calculated based on the actual flight time. On this analysis the data calculations are performed only on flight phases Take-off, Climb, Approach, and Landing. Emission Index and fuel burning data are data taken from the type and type of aircraft. Flight data obtained from flightradar24 [10] based on flight registration information in indonesia.[11]. The calculation approach is from September 18, 2022, to September 21, 2023. Fuel combustion and emission index calculations for each type of aircraft engine are obtained from ICAO (International Civil Aviation Organization) Engine Emission Database.[12].

Table 1 Parameter of Approaches to the Calculation of Emissions of Aircraft Engines

No	Key Parameters	The Advance Approach
1	Aircraft Type	Identify the type of aircraft taking-off and landing throughout Indonesia Airport using Flightradar24.
2	Machine Type	Identify group of aircraft type
3	Time in Mode (TIM)	Data Identification International Civil Organization (ICAO) certification Landing-Takeoff (LTO).
4	Emissions Index (EI)	International Civil Organization (ICAO) certification data bank values.

uses this following formula:

$$Eix = TIMx * \ Fuel\ Flow * EIx \tag{1}$$

Eix = amount of the emissions in CO2 in a fight phase x, (g);
TIMx = The amount of time during flight phase x, (s);
Fuel burn = Fuel consumption, (gg/s);
EIx = emission index in CO2, (g).

Table 2 Approach to emission calculation using aircraft type and engine type.

No	Machine Type	Fuel Flow Coefficient LTO (kg/s)	Emission Produced LTO (g/kg)		
			CO2	HC	NOx
1	CFM56-7B22E	2,127	634,696	18,0537	5856,01
2	CFM LEAP-1A26	1,815	376,460	9,88008	5572,886
3	CFM56-5B4	2,183	222,275	9,32448	6773,711
4	CFM56-3B-2	2,248	800,894	25,6881	6903,048
5	Rolls Royce Trent 768-60	6,063	1033,74	21,2652	27222,54
6	Rolls Royce Trent 772	6,490	997,417	25,0791	31396,24
7	Rolls Royce Trent 7000-72	5,213	511,990	0	37468,67
8	V2527E-A5	2,252	564,530	14,0600	7139,755
9	V2527-A5	2,056	283,136	14,0600	7139,755

4 Background of Long-Short Term Memory (LSTM)

LSTM is a type of network that adopts the model of Recurrent Neural Network structure. Recurrent Neural Network itself is a type of Artificial Neural Network (ANN), a statistical model that imitates the way that neuron cells in the human brain works. The neurons are connected through junctions called synapses. Each neuron receives thousands of connections with other neurons, constantly receiving incoming signals to reach the cell body. [8] Therefore, the architecture of the Artificial Neural Networks consist of the same parameters, there are nodes and multiple lines that connect each of the nodes. These lines have their own weights that control the calculations to affect the outputs. The earliest method of Artificial Neural Network is called Multilayer Perceptron. It has the same concept as ANN's feed-forward or forward propagation. Just like how our brain works, it does not only consist of a pair of neurons, instead every neuron will be connected to millions of neurons, and these other neurons will be connected to other neurons, so we can say that it consists of multiple layers of neurons as we can see in **figure 1**. The architecture of the MLP is completely defined by an input layer, one or more hidden layers, and an output layer. Each layer consists of at least one neuron. The input vector is processed by the MLP in a forward direction, passing through each single layer. [9] Each of the lines that connect the nodes is composed of its own weights. These weights will be then calculated by an activation function to generate the results. If the prediction went wrong, the process will be then repeated by going back to its input node. For every iteration that happens, the weights will be changed to create a more accurate result. Every iteration that happens in the process is called an epoch. However, in this paper, the main architectures are the Long Short Term Memory method, which is an advanced method of Vanilla Recurrent Neural Network (Vanilla RNN) to learn the long-term and short-term of memories.

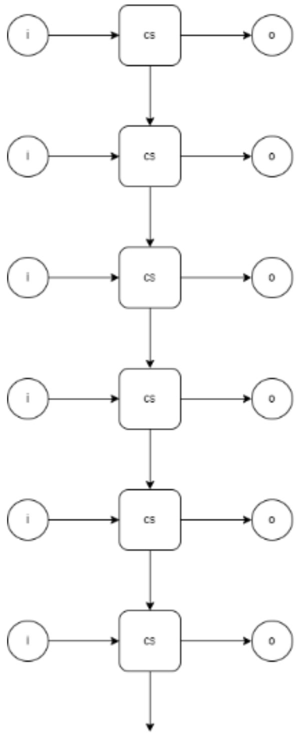


Fig .1 Simple structure of Vanilla RNN

The conventional Recurrent Neural Network (RNN) exhibits limitations in effectively handling long-term memory processes. Within the framework of the basic RNN architecture, the model's capacity to account for long-term dependencies is notably constrained. The model predominantly relies on calculating derivatives of prior outputs with respect to certain weights in order to make predictions. However, the network's intrinsic structure does not adequately account for and incorporate long-term memory elements. Consequently, this deficiency impairs the overall efficacy of the RNN in predictive tasks. This leads to a generation of new methods adopted from the vanilla RNN itself. One of these methods is called LSTM (Long-Short Term Memory) which allows the machine to consider both long-term and short-term memories by creating a new path and retrieve the output from each cell stage to be processed later on.

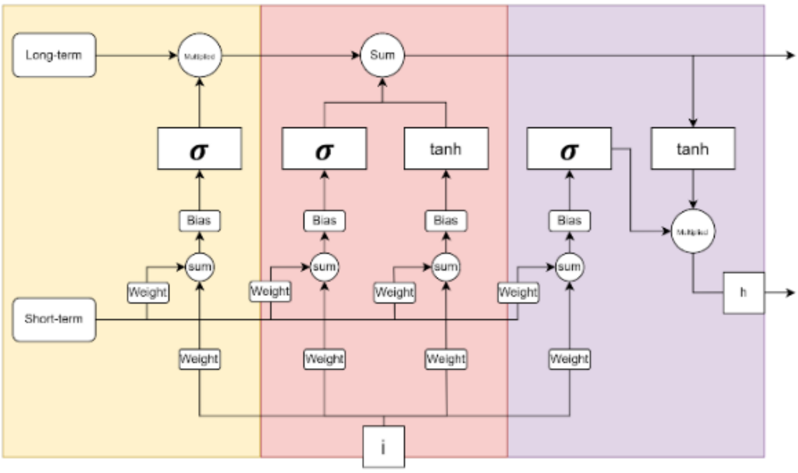


Fig 2 Structure of Long Short Term Memory

LSTM (Long Short-Term Memory) was initially introduced by Hochreiter and Schmidhuber [Jurnal 13 Filip] as a specialized type of recurrent neural network designed to effectively capture and retain information across extended sequences. This architectural innovation achieves its capabilities by preserving a continuous flow of information through dedicated cell states, ensuring the preservation of long-term data dependencies. Illustrated in the accompanying diagram, the LSTM architecture features distinct gates, namely the Forget Gate, Input Gate, and Output Gate. These gates play a pivotal role in mitigating the issue of gradient vanishing, a common challenge in conventional Recurrent Neural Network (RNN) systems, which arises from the diminishing gradients during backpropagation. This phenomenon results from the repeated application of the same transformation to input data, causing a dwindling number of gradients or errors. These calculations incorporate the sigmoid and hyperbolic tangent (tanh) functions to determine the extent to which long-term dependencies should be retained, ultimately improving the accuracy of the output. The sigmoid and tanh functions play a crucial role in this process by regulating the proportion of information to be preserved. The sigmoid function, for instance, maps values to a range between 0 and 1, effectively acting as a gate for the retention of relevant information, while the tanh function, which maps values to a range between -1 and 1, helps in controlling and shaping the flow of information. These mechanisms contribute to enhancing the overall performance and predictive capabilities of the system. The sigmoid and tanh formula can be seen as below:

$$\sigma = \frac{e^x}{e^x + 1} \tag{2}$$

$$tanh = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

As for the LSTM, the simple formula derivation illustrated in Equation _____:

$$i_t = \sigma(W_i X_i + R_i h_i + b_i) \tag{4}$$

$$f_t = \sigma(W_f X_t + R_f h_{t-1} + b_f) \quad (5)$$

$$O_t = \sigma(W_o X_t + R_o h_{t-1} + b_o) \quad (6)$$

$$g_t = tanh(W_g X_t + R_g h_{t-1} + b_g) \quad (7)$$

$$C_t = C_{t-1} f_t + g_t i_t \quad (8)$$

$$h_t = \tanh(C_t) * o_t \quad (9)$$

In the context of the model's architecture, it is essential to delineate the role of the weight parameters denoted as W_f, W_i, W_o, W_g, which represent the input weights at each computational stage, while R_f, R_i, R_o, R_g, symbolize the recurrent weights associated with each stage. These weight parameters, in conjunction with the sigmoid function denoted by, play a pivotal role in determining the degree to which long-term dependencies are retained, thereby contributing to the enhancement of prediction accuracy. The variables h_{t-1} and C_{t-1}, initially set to zero, serve as the hidden state and cell state of thse model respectively and can be subject to modification based on the underlying previous conditions. The temporal indicators, t and $t-1$, signify the current time step and the preceding step, respectively, which are instrumental in the prediction process. Additionally, the variable g_t represents a measure of potential long-term memory, playing a vital role in specifying the proportion of this information to be retained.

These parameters undergo a structured computation to ascertain the output of the long-term dependency score, culminating in the ultimate output for short-term dependency assessment. This is achieved by performing a multiplicative operation involving the hyperbolic tangent transformation of Ct (memory cell state) and ot, contributing significantly to the final output and capturing the dynamics of long-term and short-term dependencies within the model's context.

5 Application of Gated Recurrent Unit (GRU)

GRU stands for Gated Recurrent Unit, a similar method to LSTM adopted from Recurrent Neural Network (RNN). This method uses two main gates, update gate and reset gate. Reset gate is responsible for deciding which data to remember and which to forget, a similar system as the forget and input gate of LSTM. Update gate is responsible to decide the quantity of the passed information to forget – similar to the tanh function of the input gate of LSTM. The structure of the **figure 3** is shown below:

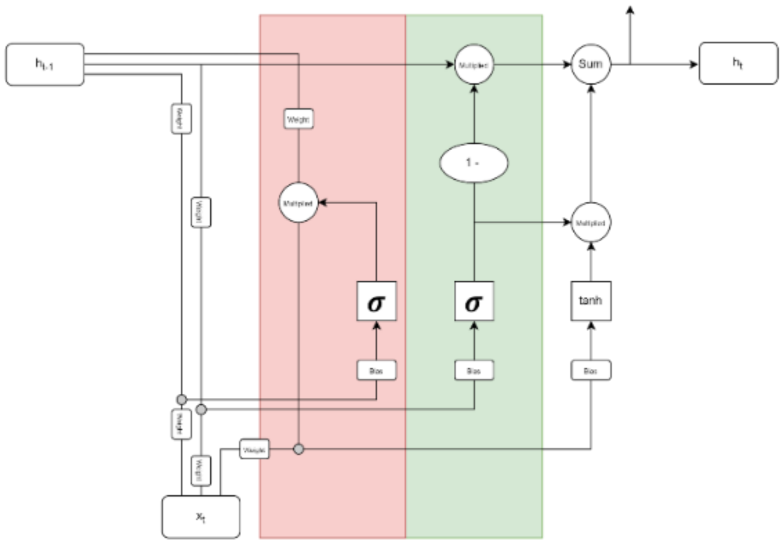


Fig 3 Structure of Gated Recurrent Unit (GRU)

The schematic representation differentiates between the reset gate, denoted by the red area, and the update gate, identified by the green section. It's noteworthy that the mathematical framework employed in this methodology closely resembles that of the Long Short-Term Memory (LSTM) model, as depicted in the formula presented below:

$$u_t = \sigma(W_u X_t + R_u h_{t-1} + b_u) \tag{10}$$

$$r_t = \sigma(W_r X_t + R_r h_{t-1} + b_r) \tag{11}$$

$$C_t = \tanh((R_c h_{t-1} * r_t + W_c x_c) + b_o) \tag{12}$$

$$h_t = (u_t * C_{t-1}) + ((1 - u_t) * h_{t-1}) \tag{13}$$

This model demonstrates the potential for enhanced efficiency when compared to LSTM. The streamlined design of the gates simplifies the process, facilitating swifter information flow. However, it is worth noting that GRU diverges from LSTM in that it lacks a dedicated cell state. Instead, it relies solely on the hidden state for information transfer. This distinction implies a trade-off, as it offers speed but reduces the ability to explicitly control the memory unit.

6 Simulation and Results

The simulation was conducted utilizing Keras, a specialized Application Programming Interface within the TensorFlow framework, tailored for addressing complex machine learning challenges. In tandem with Keras, two pivotal libraries were employed to streamline the process:

Pandas, which served as a versatile data manipulation tool for enhancing data organization, and Numpy, instrumental for array transformations central to numerous computational tasks. Furthermore, the visualization component was facilitated through the utilization of Matplotlib, a widely adopted Python library renowned for its graph plotting capabilities.

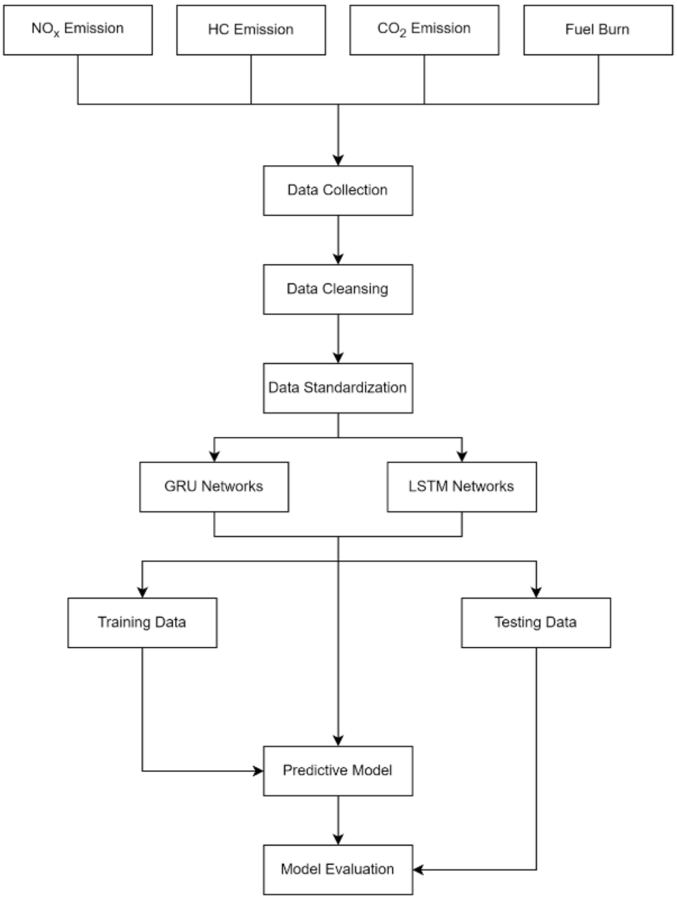


Fig 4 Workflow of LSTM Emission Prediction

6.1 The Dataset

Recurrent Neural Network can only be implemented by using time-series data, thus in this paper we used data from FlightRadar24 and public dataset from International Civil Aviation Organization (ICAO). The range of the time-series span from 18th September 2022 to 21st September 2023 in this paper. The data then splitted into a 70:10:20 of training, validation, and testing data respectively with the features as shown below:

Table 3 The parameter of approach method

Feature	Summary
Date	Date recorded of flights.
Fuel burn	The fuel required in all flights in a particular date cumulatively.
CO_2	Value of CO_2 emitted for all flights cumulatively.
HC	Value of HC emitted for all flights cumulatively.
NO_x	Value of NO_x emitted for all flights cumulatively.

The dataset would then be splitted into 3 different categories, testing, training and validation data. These sets of data are required to perform a prediction model under the machine learning environment. Along with this simulation, these parameters are considered. The optimizer that was used in this research is the Adam optimizer, one of Keras' algorithms to optimize the learning rates of each parameter, making the process converge faster. The input and output layer = 10 (based on inputs – how many historical data to be processed on each step), along with two LSTM layers = 26 and 13 units, Dense Layer = 4 (based on the features). The similar model goes for GRU with 1 layer of input, 2 layers of GRU along with a Dropout layer to minimize possibilities of underfitting or overfitting, and 1 Dense layer as output. In order to optimize the learning rates of each gradient, we also deployed Adam Optimizer. The **figure 5** below shows the visualization of the raw data without

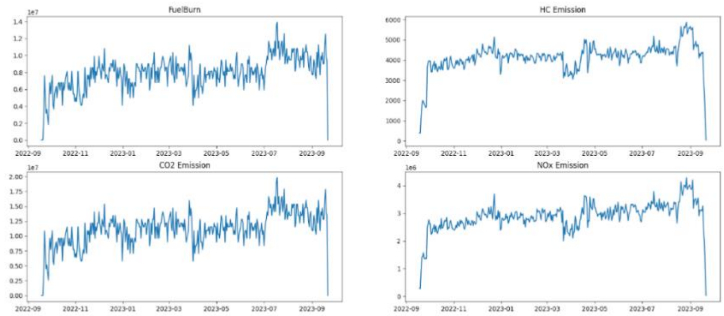


Fig 5 Raw Emission Time-series data

By looking at the Loss – validation and training loss – we could determine whether the training process went well or not. The training loss and the validation loss have to be in a state where both of the values are close to each other. If the values of both losses do not tangent to each other, the prediction is going to be inaccurate due to either overfitting or underfitting, a state where one of the parameters is lower than the other. The paper used regularizer, a method done by adding a cost to the loss function associated with having large weights resulting in distribution of weight values to be regular by only taking small values to the weights. In this paper, the regularization used was L2 Regularization.

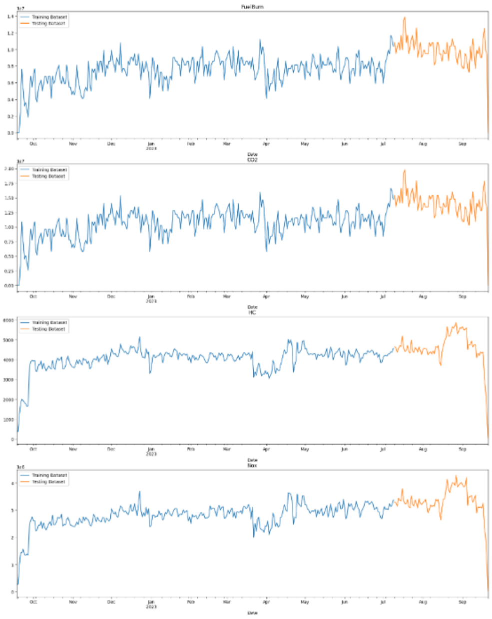
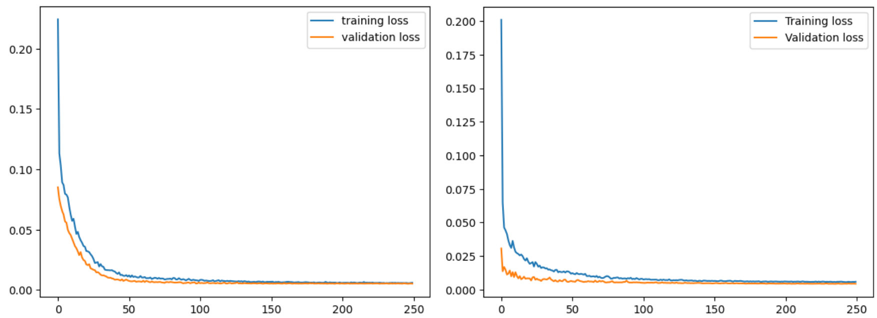
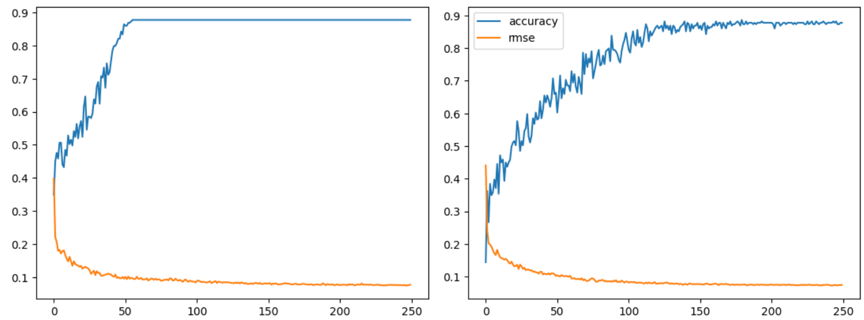


Fig 6 Train-test split (80% train)

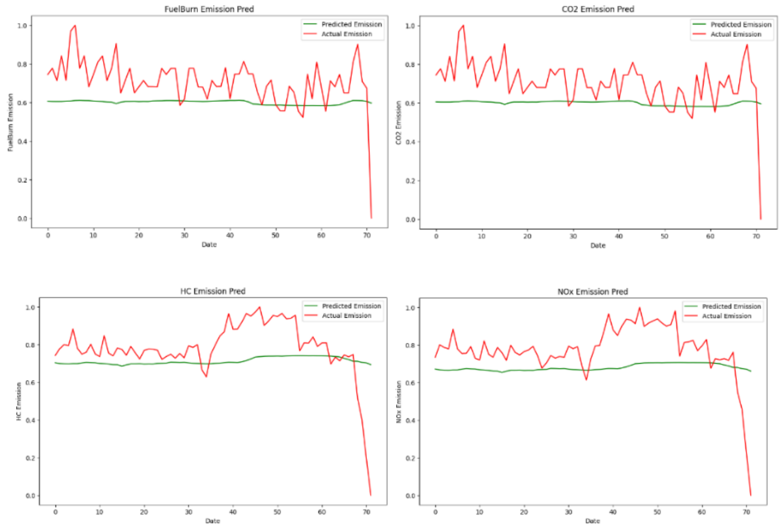


(a)



(b)

Fig 7 (a) LSTM and GRU trained data loss and validation loss progress **(b)** LSTM and GRU RMSE and accuracy on training progress.



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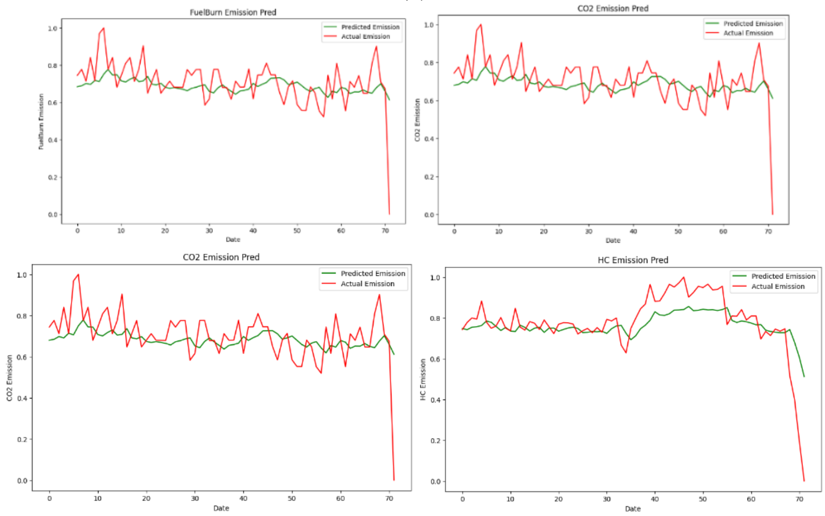

(b)

Fig 8 (a) The prediction of the emission flow with LSTM **(b)** The prediction of the emission flow with GRU.

The result that we received did not meet our expectations as the predictions only have 48% for LSTM and 56% for GRU on average. However, this model can go up to 87% accuracy as it surges on iteration. LSTM took up 50 iterations in order to get the expected accuracy, as for GRU took up 200 iterations, which is not very desired. Therefore, we tend to scale up the quantity of the inputs (the historical data) and increase the hidden layer by one. **Figure 9** and **Figure 10** shows the result of the better RMSE and prediction which have an increasement by 2% for

LSTM, as for GRU decrease by 4%. The model also shows a low number of RMSE reached down to 1.6% for LSTM and 1.1% for GRU.

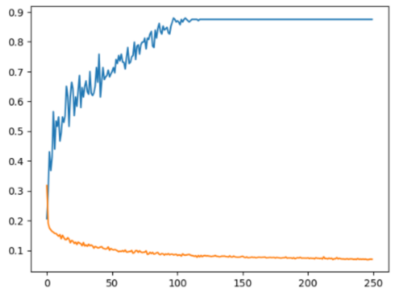

Fig 9 LSTM RMSE

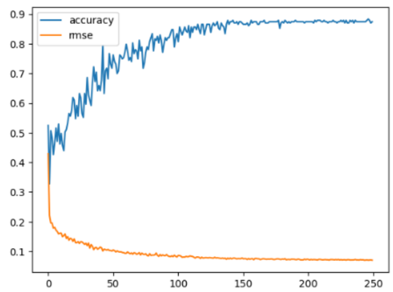

Fig 10 GRU RMSE

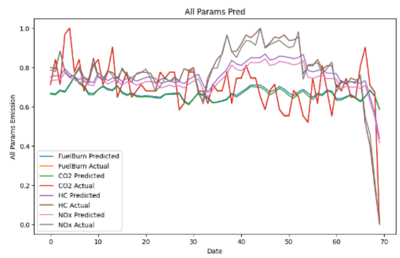

Fig 11 LSTM with 3 hidden layers

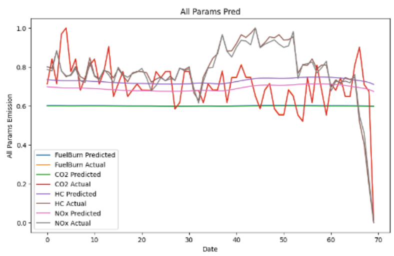

Fig 12 GRU with 3 hidden layers

7. Conclusion

The emissions generated by aircraft are subject to significant variability, primarily influenced by factors such as the specific flight parameters and the type of fuels employed. This variation in emissions has prompted the development of a machine learning model tailored for the aviation sector. The proposed model aims to effectively suppress the unpredictable fluctuations in emissions, contributing for more sustainable aviation industry. By harnessing the power of data-driven insights and real-time monitoring, this model has the potential to play a crucial role in mitigating the environmental impact of aviation, ultimately leading to a cleaner and more eco-friendly future for air travel. Therefore, Emission Prediction based on LSTM and GRU model is proposed using some tuning to achieve a 87% accurate prediction of the data that were cumulatively generated in Indonesia.

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