Aviation Carbon Emissions Forecasting and Carbon Credit Trading

A PROJECT REPORT

SUBMITTED TO
SVKM'S NMIMS (DEEMED- TO- BE UNIVERSITY)

IN PARTIAL FULFILLMENT FOR THE DEGREE OF

BACHELORS OF SCIENCE
IN
DATA SCIENCE

BY

AGRIMA JAIN
AYUSH MANTRI
DEEP SOLANKI
JASH MOZE
SIMRAN S CHIKKALA

NILKAMAL SCHOOL OF MATHEMATICS, APPLIED STATISTICS & ANALYTICS

NMIMS NSOMASA
Ground Floor, SBMP Phase I,
Irla, N. R. G Marg, Opposite Cooper Hospital,
Vile-Parle (West), Mumbai – 400 056

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Program Chairperson (Data Science)
(Prof. Shraddha Sarode)

Dean
(Dr. Sushil Kulkarni)

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CERTIFICATE

This is to certify that work described in this thesis entitled "**Aviation Carbon Emissions Forecasting and Carbon Credit Trading**" has been carried out by Ms. Agrima Jain, Mr. Ayush Mantri, Mr. Deep Solanki, Mr. Jash Moze and Ms. Simran S Chikkala under my supervision. I certify that this is their bonafide work. The work described is original and has not been submitted for any degree to this or any other University.

Date:
Place:

SUPERVISORS
(Dr. Kavita Jain &
Prof. Pratik Desai)

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Thank you for your unwavering support.

ABSTRACT

The aviation industry is an important contributor to global carbon emissions, which requires accurate prediction models and efficient mitigation strategies. This project integrates real-time flight and weather data to estimate carbon emissions and predict carbon credit prices. Our method improves emissions estimation accuracy by using deep learning models, establishing the foundation for a dynamic carbon trading model. The model ensures that emissions data is transformed into useful measures, enabling transparent and efficient carbon credit trading. By offering a data-driven framework for emissions estimation and carbon market simulation, this project aims to support sustainable aviation by ensuring conscious carbon credit usage across airlines.

Keywords: Carbon Emissions, Deep Learning, Reinforcement Learning, Sustainable Aviation, Carbon Market Simulation.

INTRODUCTION

Climate change and environmental sustainability have become topmost global issues over the last few years, forcing governments and institutions to seek novel mechanisms to minimize carbon emissions. The aviation sector is one of the major carbon emitters worldwide, among all the efforts to reduce carbon emissions, carbon trading markets have emerged as a major mechanism, through which companies can purchase and sell carbon credits as a means to offset their emissions and encourage green practices. In a carbon trading system, governments or regulatory authorities impose a general limit on emissions and allocate or auction carbon credits to firms. Each credit entitles the owner to release a specified amount of carbon dioxide or equivalent gases. The organizations that are successful in lowering their emissions below their quota can sell their surplus credits to others, thus providing an economic incentive for ecologically sound operations.

Still, the efficiency of traditional carbon markets is frequently dependent on proper emissions reporting, manual tactics and prompt trading moves - domains typically hampered by lags, manual processes and limited forecasting abilities restricting their response to real-time operational and environmental dynamics.

With the increasing data-driven nature of industries, there is greater necessity to revamp the carbon trading systems to render them more dynamic, real-time, and responsive to functional enhancements. Automation of carbon trading may allow for enhanced forecasting, faster decision-making, and enhanced carbon asset management, ultimately aiding industries in achieving business objectives as well as environmental objectives in a more effective way.   This research intends to make an input towards this modernization by suggesting a model for an automated system of carbon trading.

The project is intended to develop an operative prototype incorporating real-time data gathering, emission forecasting, and adaptive trading mechanisms.

The model mimics a system in which information like flight operations and weather conditions can be used to forecast carbon emissions and guide intelligent trading decisions. By automating key elements of the carbon market, the suggested framework hopes to provide the foundation for more intelligent, quicker, and more accurate carbon management systems in the future. With a focus on aviation, this study provides the foundation for automated carbon trading platforms specific to the industry, furthering the larger push for effective and sustainable carbon emissions management across industries.

AIMS AND OBJECTIVES

- To demonstrate the practical application of Deep Learning, and Reinforcement Learning techniques in the aviation sector, highlighting the potential of AI-driven methods to support future sustainable aviation carbon management strategies.
- To study how flight parameters, such as distance to destination and weather conditions (humidity, wind speed, temperature), impact carbon emissions, and in turn, the number of carbon credits required.
- To estimate the carbon emissions generated by flights and predict the associated carbon credit prices.
- To build a reinforcement learning-based trading model that can make optimized decisions on buying, holding, or selling carbon credits, simulating dynamic market conditions and help explore strategies for maximizing profits while promoting sustainability.

LIMITATIONS

- **Limited Flight Data from Free APIs:**
  The OpenSky Network API (flight data) and OpenWeatherMap API (weather data) free versions limit us to 25 aircraft per day. This forced us to collect data over time, potentially missing broader flight patterns and introducing gaps or bias.

- **Challenges with CNN and YOLO for Flight Path Tracking:**
  We planned to use CNN or YOLO for visual flight path analysis but couldn't due to the need for video data. OpenSky provides only snapshots, not continuous paths, and alternatives like Google Earth are paid and computationally costly.

- **Computational Constraints:**
  Limited resources restricted Reinforcement Learning model training to 10,000 timesteps and capped flight processing at 500. Scaling to more flights or advanced models (e.g., CNNs) was unfeasible due to hardware limitations.

- **Lack of Real-Time Video or Path Tracking:**
  Continuous flight path tracking was impossible with available APIs, which offer point-in-time data only. Video-based tracking (e.g., via satellite) was impractical due to cost and lack of accessible data.

- **Scalability Issues:**
  Processing is limited to 500 flights at a time. Expanding to global monitoring requires more robust data systems and power, which were beyond our project's scope.

SCOPE OF RESEARCH

- **Complete Flight Path and Real-Time Tracking:**
  Integration APIs that provide total flight paths (with confirmed destinations) and ongoing real-time tracking would eliminate destination estimation, resulting in better distance and emissions calculations.

- **Live Carbon Pricing and Dynamic Trading:**
  Utilizing real-time APIs for carbon pricing would facilitate live valuation and trading of carbon credits, and the model can be used in real market applications rather than using synthetic price trends.

- **Improved Emissions Precision:**
  The use of plane-specific information (such as aircraft type and engine efficiency) in combination with computer vision algorithms (e.g., CNN or YOLO) for path analysis—if visual data is available—would enhance the accuracy of emission estimates.

- **Integration with Airline Operations and Policy Analysis:**
  The system may be able to assist airlines in maximizing routes and fuel consumption to lower emissions and trading expenses. It may also simulate the impacts of government policy and carbon pricing policies on airline actions and emissions.

LITERATURE REVIEW

The aviation industry is a significant contributor to global carbon emissions, making it crucial to develop accurate prediction models and efficient carbon credit trading mechanisms. Over the years, several studies have explored different aspects of aviation-related carbon emissions, from predictive modelling to policy-driven market-based approaches. Our research builds upon these prior works while introducing a novel methodology that integrates OpenSky flight data and weather data from OpenWeatherMap for enhanced prediction accuracy and the development of a trading framework for carbon credits.

In a study [1], a hybrid short-term carbon emissions prediction model for China's aviation sector was introduced using a decomposition-prediction approach. Their model demonstrated improved predictive accuracy over existing models. While their work relied on historical aviation trends, we extend the predictive capabilities by integrating real-time flight and weather data, enabling dynamic emissions estimation.

Research [2] analysed the economic feasibility of a sustainable aviation fuel (SAF) supply chain, incorporating carbon credits as an incentive for emission reduction. Their study focused on SAF production and carbon credit integration, whereas our research develops a trading model for carbon credits based on real-time emission predictions rather than fuel sourcing strategies.

A study [3] explored the use of machine learning for financial risk management and fuel efficiency improvements in aviation operations. Their work provided insights into applying machine learning for fuel consumption prediction. We extend this approach by incorporating machine learning not only for fuel efficiency but also for predicting emissions and carbon credit valuations, enhancing market applicability.

An overview of the EU Emissions Trading System (ETS) was provided in research [4], which proposed a data-driven methodology using the Hankel Alternative View of Koopman (HAVOK) algorithm to forecast carbon prices. While their model focused primarily on carbon pricing prediction, we integrate additional real-time variables such as weather conditions and flight trajectories to enhance the predictive accuracy of carbon credit trading.

A study [5] developed a high-resolution emission inventory using real-world flight trajectory data, enabling a detailed spatiotemporal characterization of emissions in China's aviation sector. While their work created a static emission inventory, our research enhances this by generating dynamic real-time emissions predictions using OpenSky flight data.

Research [6] proposed a market-based framework for CO_2 emissions reduction in China's aviation sector, leveraging economic incentives to drive sustainability. While their study focused on policy implementation, our research ensures that emission predictions translate directly into actionable economic opportunities through carbon credit trading.

A study [7] introduced a computer vision-based system for autonomous aircraft taxiing, reducing emissions associated with ground operations. While their work targets taxiing efficiency, our focus remains on airborne emissions, utilizing predictive modelling and trading mechanisms to mitigate environmental impact.

Research [8] explored carbon price prediction using a scaled PCA (s-PCA) approach, demonstrating superior performance in forecasting carbon prices over traditional methods. We incorporate similar scalable machine learning techniques in our carbon credit trading model to optimize credit valuations based on emissions data.

A study [9] investigated the impact of carbon trading policies on corporate carbon emission intensity, highlighting the moderating role of ESG performance. While their research examined policy implications, our study provides a data-driven foundation for carbon credit pricing, fostering transparency and efficiency in the trading market.

In summary, our study builds upon existing research by integrating real-time flight and weather data into carbon emissions prediction models. Furthermore, we extend prior economic analyses by developing a comprehensive trading model for carbon credits, ensuring that emissions data directly informs market-based mechanisms.

METHODOLOGY

To accurately predict carbon emissions in aviation, we developed a structured approach that integrates real-time flight and weather data with machine learning techniques.

Collecting and Integrating Data

We started by extracting real-time flight data from the OpenSky API, which gives us crucial parameters like latitude, longitude, velocity, altitude, and callsign. To factor in the environmental conditions, we also extracted weather data—temperature, humidity, and wind speed—from OpenWeatherMap API. Since we needed to determine each flight's destination, we matched the aircraft's coordinates with the closest airport using the data from Flight Tracker API. While this approach assumes the nearest airport is the final destination, as the data updates, it remains dynamic.

Calculating Distance

With a structured, merged dataset containing flight details and weather conditions, we calculated the distance between an aircraft's current position and its estimated destination. We used the Haversine formula, which provides an accurate great-circle distance based on latitude and longitude coordinates.

Estimating Carbon Emissions

To predict emissions, we followed a series of computations:

- **Burn Rate Calculation:** We estimated the fuel burn rate based on the aircraft's velocity, Burn Rate = velocity*0.02
- **Fuel Consumption:** Using the burn rate and flight distance, we calculated the total fuel burnt per kilogram, Fuel Consumed = Burn Rate*Distance
- **Emissions Computation:** Since jet fuel has a CO_2 factor of 3.16, we multiplied the fuel burnt by this factor to determine total emissions.
- **Credits Needed:** Carbon credits were calculated by dividing total emissions by 1000, representing the number of credits required in proportion to the flight's emissions.

Estimating Carbon Price

Since historical carbon price data wasn't available, we simulated a random sequence of carbon price variations using NumPy's random function. We then applied the ARIMA model to predict the next day's carbon price, mimicking the fluctuations observed in real-world carbon trading markets. Finally, we calculated the total credit cost by multiplying the predicted carbon price with the required credits.

Predicting Carbon Emissions

We implemented advanced Deep Learning models to predict the carbon emissions more dynamically and to capture temporal patterns and dependencies in flight movement and environmental factors, based on our real-time data.

We used models like,

LSTM - Recurrent Neural Network designed to learn long term dependencies, ideal for sequential data.

ConvLSTM – An extension of LSTM that integrates convolutional operations, making it better suited for learning spatial and temporal correlations.

GRU - A streamlined variant of LSTM that uses fewer parameters, allowing faster training while still capturing temporal patterns effectively.

DNN – A Deep Neural Network composed of multiple fully connected layers, capable of learning complex patterns from high-dimensional data.

Model Architecture

Each model was modified to pick up on various patterns and dynamics in the data:

1. LSTM Model

LSTM model was formulated to extract temporal dependencies in the data.
Architecture:

- Two LSTMs stacked together (128 and 64 units) with recurrent dropout for regularizing.
- A Batch Normalization layer to achieve stable learning.
- Dense layers (32 units and final output) to project learned features to carbon emissions.
- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam with learning rate 0.0005.

2. GRU Model

The GRU model, a lightweight version of LSTM, was also employed for sequence learning.
Architecture:

- Two GRU layers (128 and 64 units) with recurrent dropout.
- Batch Normalization for stability.
- Dense layers (32 units and output layer).
- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam with a learning rate of 0.0005.

3. ConvLSTM Model

As both spatial and temporal correlations were to be utilized, a ConvLSTM model was constructed.
Architecture:

- Two ConvLSTM2D layers (64 and 32 filters) with a kernel size of (1, 3) and padding.
- Batch Normalization layers after every convolution.
- Flattening followed by Dense layers (64 units) and final output.
- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam with a learning rate of 0.0005.

4. Deep Neural Network (DNN)

A fully connected feedforward DNN was employed for tabular feature-based prediction as well.
Architecture:

- Input layer for the 6 chosen features (altitude, velocity, humidity, fuel burn, distance, wind speed).
- Three hidden Dense layers (128, 64, 32 units) with ReLU activation and dropout for regularization.
- A final Dense output layer for predicting emissions.
- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam with a learning rate of 0.001.

Comparative Analysis: We compared the performance of LSTM, GRU ConvLSTM and DNN to select the most accurate model for emissions forecasting.

By following this approach, we successfully developed a real-time carbon emissions prediction model based on flight and weather data. This forms the foundation for the next phase—building a dynamic carbon credit trading model that can efficiently price and trade emission credits based on real-time predictions.

Building Carbon Credits Trading Model

To build a carbon credit trading model we used reinforcement learning. A custom environment was created where the agent could buy, sell, or hold carbon credits based on flight and weather-related features. The models were trained to maximize trading profits over time, using algorithms like PPO

(Proximal Policy Optimization), A2C (Advantage Actor-Critic), and SAC (Soft Actor-Critic).

- **PPO (Proximal Policy Optimization):** Balances exploration and exploitation by limiting large policy updates, making it stable and reliable for training.

- **A2C (Advantage Actor-Critic):** Uses both a policy and an Advantage function to improve learning efficiency, offering faster but sometimes less stable convergence.

- **SAC (Soft Actor-Critic):** Introduces entropy regularization to encourage exploration, leading to more robust performance in environments with high uncertainty.

After training, the models simulated trading actions and adjusted the final balance accordingly, helping optimize carbon credit management.

Model Architecture

1. Proximal Policy Optimization Model

The PPO model was built in order to balance exploration and exploitation while ensuring stable policy updates.
Architecture:

- Independent Actor and Critic networks.
- Actor: Three fully connected layers (128, 128, output = size of action space) with ReLU activations.
- Critic: Three fully connected layers (128, 128, output = single value) with ReLU activations.
- Clipped Surrogate Objective for the actor.
- Mean Squared Error (MSE) loss for the critic.
- Optimizer: Adam optimizer with learning rate 0.001.

2. Advantage Actor-Critic Model

The A2C model was introduced to learn value functions and policies concurrently for effective learning.
Architecture:

- Shared feature extractor: Two fully connected layers (128, 128) with ReLU activations.
- Actor head: A fully connected layer projecting responses (shared features) into action logits (output = action space size).
- Critic head: A fully connected layer projecting responses (shared features) to a single value output.
- Actor Loss: Policy gradient loss (with Advantage estimates used).
- Critic Loss: Mean Squared Error (MSE) between predicted and true returns.
- Entropy Bonus added to support exploration.
- Optimizer: Adam optimizer with learning rate 0.001.

3. Soft Actor-Critic Model

The SAC model was created to maximize expected reward while encouraging exploration through entropy regularization.
Architecture:

- Actor network: Three fully connected layers (256, 256, output = action space size) with ReLU activations.
- Two Critic networks (Critic 1 and Critic 2): Each with three fully connected layers (256, 256, output = 1) with ReLU activations.
- Independent Target Networks for Critics to stabilize training.
- Mean Squared Error (MSE) loss for critic networks.
- Policy Loss: Minimization of expected KL-divergence with entropy term to promote exploration.
- Optimizer: Adam optimizer with learning rate 0.001.

DATA DESCRIPTION AND ANALYSIS

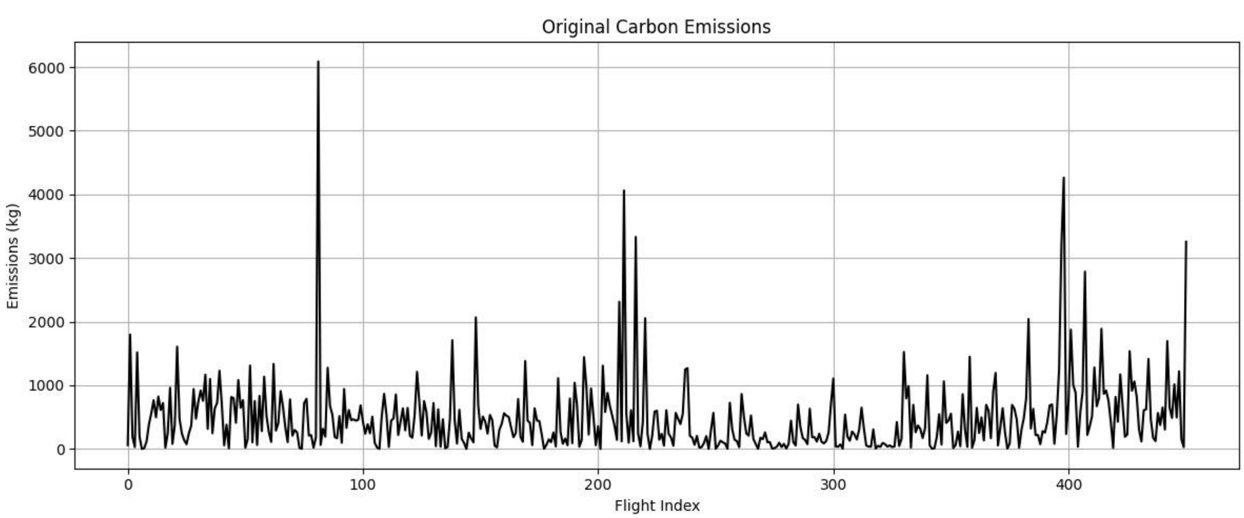
The dataset focuses on aircraft-level emissions monitoring and prediction using both environmental and flight-related parameters. Below is a breakdown of the key features:

Feature	Description
icao24, callsign	Unique aircraft identifiers
longitude, latitude, altitude, velocity	Real-time flight position and speed data
distance_km	The aircraft's distance from destination
temperature, wind_speed, humidity	Environmental conditions surrounding the aircraft
burn_rate	Fuel consumption rate (kg/s or similar)
fuel_burn_kg	Total fuel consumed
emissions_kg	CO_2 emissions in kilograms (target variable)
credits_needed, credit_cost_usd	Carbon credits required and the associated cost.

Target Variable: Emissions Analysis
The target variable emissions_kg reflects the CO_2 output per flight.
As shown in the emissions plot below, the distribution is highly variable with multiple spikes, suggesting the presence of:

1. Long-haul or high-altitude flights producing greater emissions
2. Potential outliers or special conditions, like weather anomalies or detours

This non-stationarity and variability makes it a suitable candidate for modelling with temporal deep learning models like LSTM, GRU, and ConvLSTM or DNN, which can capture complex nonlinear sequences over time.



RESULTS AND DISCUSSION

We deployed and compared LSTM, GRU, Convolutional LSTM and Deep Neural Network models to assess the prediction accuracy of deep learning models in quantifying carbon emissions per flight.

The models were tuned on a preprocessed data set with salient flight features like emissions_kg, fuel_burn_kg, temperature, wind_speed, and credit_cost_usd. Both qualitative observations and quantitative measures like Root Mean Squared Error (RMSE) and the coefficient of determination (R^2 score) were used to measure performance.

LSTM Model Performance

Among all the tested architectures, the LSTM model exhibited better performance in modeling both short- and long-term dependencies of the emission data. As illustrated in the respective figure, the predicted emission values by using LSTM track the actual values well in most time steps. Though there were slight underestimations in the case of sharp spikes, the overall agreement between predicted and actual emissions proves that the model successfully learned the temporal patterns.

LSTM's power is its gating mechanism (input, forget, and output gates), which allows it to retain and eliminate information over time. This is especially useful for flight data, where velocity, altitude, and environmental conditions keep changing over time.

ConvLSTM Model Performance

The ConvLSTM model provided smoother forecasts but failed to capture the magnitude and volatility of the real emissions. Although it attained a relatively low RMSE of 0.0778, the R^2 measure was 0.3850, signifying poor variance explanation ability in the real data. This underperformance can be explained due to the character of ConvLSTM architecture, which is designed for spatiotemporal data—like satellite images or video frames—instead of strictly sequential tabular data. Consequently, even though it could produce smooth output, ConvLSTM didn't generalize well to the unique structure and temporal relationships in the flight emissions dataset.

GRU Model Performance

The GRU model performed moderately—better than ConvLSTM but not quite as well as LSTM. GRU is computationally more efficient due to its reduced architecture, but that is at the expense of poorer memory retention. The model performed well with the ability to follow local oscillations but was poor with the ability to follow abrupt changes, which negatively impacted its ability to make sound long-range predictions.

Deep NN Model Performance

The Deep Neural Network (DNN) model, though not explicitly designed for sequential data, did very well with the simplicity of its architecture and its ability to map directly between inputs and outputs. It had an RMSE of 201.6111 and an R^2 score of 0.8555, indicating great predictive power.

DNN models work by learning nonlinear relationships using dense layers without actually modeling time dependencies. This renders them appropriate for issues in which the input data includes enough patterns that may be acquired without the need for temporal memory. Here, the DNN was capable of generalizing fairly well across the majority of the instances, though it did not have the sensitive treatment of time-based dependencies that recurrent models provide. Consequently, though its R^2 score was excellent, it did not surpass the LSTM model in overall emission prediction.

Deep Learning Model Comparison

A performance summary of the deep learning models is shown in the table below:

Model	RMSE	R^2 Score	Strengths	Limitations
LSTM	0.0390	0.8976	High accuracy, strong temporal modeling	Minor underestimation of extreme peaks
ConvLSTM	0.0776	0.3883	Smooth predictions	Poor generalization to sequential data
GRU	0.0641	0.5830	Computational efficiency	Struggles with sharp transitions
DNN	201.6111	0.8555	Good fit on overall trends, fast interference	Lacks memory of temporal dependencies

LSTM performed better than GRU and ConvLSTM due to its capacity for retaining long-range dependencies and its resistance to vanishing gradient issues. This enables it to make sound predictions based on data points appearing very much earlier in time. While DNN achieved a strong R^2 Score, its lack of memory mechanisms made it less suited for capturing temporal dynamics. Conversely, ConvLSTM, is better at spatial patterns, and GRU's less complex gating can cause significant information to be lost too early or oversimplified the sequential structure.

Reinforcement Learning Model Performance

Besides deep learning models, we introduced three reinforcement learning models—Soft Actor-Critic (SAC), Advantage Actor-Critic (A2C), and Proximal Policy Optimization (PPO)—to simulate carbon credit trading strategies using emission data. The table compares each model based on final balance, total emissions, reward trend, and its strengths and limitations.

- SAC showed consistent progress in episodic reward from −27,900 to −5,590 over 9,260 timesteps. Its actor loss converged from +14.2 to −54.5, while the critic loss fluctuated, showing some instability in Q-value estimation. Notwithstanding this, SAC registered the minimum cumulative emissions (69231.94 kg) while ensuring a fair final balance of $10,000.00. This equilibrium between environmental and economic efficiency makes SAC the best model overall in this scenario.

- A2C, as an on-policy algorithm, provided a consistent reward pattern but converged prematurely, with the end balance being $9810.71 and maximum emissions (69631.94 kg). Its restricted exploration might have resulted in poor long-term policies.

- PPO had the highest last balance of $9925.19, thanks to aggressive exploration and robust policy updates. But its emissions were somewhat higher (69331.94 kg) than SAC's and it had high value loss variance, so it was less consistent even though it remained profitable in the short term.

Model	**Final Balance ($)**	**Total Emissions(kg)**	**Reward Trend**	**Strengths**	**Limitations**
PPO	$9925.19	69331.94	Fluctuating	High profitability, strong exploration	High loss values
SAC	$10,000.00	69231.94	Steady improvement	Stable actor learning	No actual gain, conservative strategy
A2C	$9810.71	69631.94	Flat/stable	Simple and efficient	Low exploration, local optima

The findings show that LSTM is significantly effective for time series prediction. Of carbon credit trading scenarios, PPO and SAC can be useful in dynamically responding to dynamically changing carbon credit trading scenarios. A hybrid system combining predictive (such as LSTM or DNN) and policy (such as SAC) models might be able to maximize both emissions forecasting and strategic decision-making in carbon markets—preparing the basis for real-time monitoring of emissions and sustainable development of aviation policy.

CONCLUSION

The findings demonstrate that LSTM is particularly effective for flight emissions, as a result of its ability to retain long-term dependencies and model temporal patterns accurately. In the context of carbon credit trading simulations, reinforcement learning models—especially PPO and SAC—show promise for dynamically responding to fluctuating environmental and economic conditions. PPO, in particular, exhibited the highest profitability, although it involved more volatile training dynamics.
Overall, integrating LSTM for emissions forecasting and PPO for trading strategy optimization presents a compelling approach toward developing an intelligent and adaptive carbon management systems in the aviation sector.

In summary, the integration of predictive modelling and reinforcement learning, and by accurately forecasting emissions and optimizing trading strategies, the developed framework demonstrates the potential for efficient and responsive carbon management in the aviation sector.
These results reinforce the value of data-driven approaches in tackling complex, real-world problems where dynamic decision-making is crucial.

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