Introduction:

Machine Learning (ML) has become a very proficient way of making predictions using our computational resources to best overcome and adapt to real-life scenarios. Many of said scenarios can be cumbersome due to the copious quantities of data that must be sifted through to create a valuable and well-trained model. Our project focuses on leveraging ML to analyze and predict patterns within airport traffic data, specifically using datasets provided by the FAA’s Traffic Flow Management System Counts (TFMSC) website. This data offers valuable insights into airport operations, including flight volumes, passenger capacity per aircraft, and other metrics that impact the aviation industry. However, the dataset originally included numerous columns that were extraneous to our analysis. Sifting through these columns to extract only the most relevant features required careful consideration and domain knowledge, ensuring that the dataset was streamlined for modeling without losing critical information. The HARAMBE model or Hurricane Alert and Resource Allocation for Managing Buffer-zone Evacuation, is a model that will automatically choose what resource, in other words available aircraft/ flight, can be allocated to the zone that is going to be impacted by the approaching hurricane. For training and testing as of now, our project is using the data acquired during Hurricane Ian in 2022.

Analyzing our model further, the HARAMBE model represents a novel application of ML in disaster management and resource optimization. By analyzing historical data and leveraging the predictive capabilities of ML, this model will be able to produce the results necessary to meet our goal. During Hurricane Ian in 2022, significant challenges arose in managing evacuation efforts due to the unpredictable nature of the storm and the high demand for flights out of affected areas. The data collected from this event provided a unique opportunity to train our model to better understand the patterns and dynamics of such scenarios, enabling us to develop a system that could mitigate chaos and improve coordination in future emergencies.

The overarching objective of the HARAMBE model is to create a tool that not only saves lives but also optimizes the use of resources in a cost-effective manner. In the context of Florida, a state particularly vulnerable to hurricanes, this model could significantly enhance the ability of airports and airlines to respond to natural disasters. By predicting demand, identifying available resources, and recommending efficient allocation strategies, the model could help mitigate injuries and death, minimize financial strain on airlines and passengers, and ensure a more organized evacuation process.

Related Works:

Evaluation of the aircraft fuel economy using advanced statistics and machine learning, particularly concerning fuel efficiency, and the points below explores how a Recurrent Neural Network (RNN) model could be used to potentially produce better results and generate new outcomes compared to other Machine Learning (ML) models.

The article emphasizes the importance of fuel efficiency in the airline industry and the challenges in accurately assessing the impact of retrofits on fuel consumption. Let's examine the key aspects and how an RNN could be beneficial:

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**Fuel Economy Monitoring:** The article introduces three key performance indicators commonly used to monitor fuel efficiency: Specific Range (SR), Fuel Used (FU), and Fuel Burn Off (FBO)1. These indicators rely on data collected during flight, which can be influenced by various factors such as measurement errors and turbulence.

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**RNN Application**: An RNN could be trained on historical flight data, including fuel consumption, flight parameters (speed, altitude, etc.), and weather conditions. The RNN's ability to process sequential data makes it well-suited to analyze time-series data like flight data, potentially learning complex relationships between these factors and fuel efficiency. This could lead to more accurate predictions of fuel consumption for specific flight routes and conditions.

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**Measurement Errors and Uncertainties:** The article discusses different types of measurement errors, including systematic, dynamic, and stochastic errors, that can affect fuel efficiency calculations23. Turbulence is also highlighted as a factor that introduces uncertainties4.

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**RNN Application**: RNNs can be effective in dealing with noisy data. They can learn to filter out noise and identify underlying patterns in the data, potentially mitigating the impact of measurement errors on fuel efficiency predictions. Furthermore, by incorporating turbulence data as an input feature, the RNN could potentially learn to account for its impact on fuel consumption.

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**Quantification of Fuel Efficiency Increase of Retrofits:** The article focuses on the difficulties in accurately quantifying the fuel efficiency gains from implementing retrofits5. This is particularly challenging for retrofits with small performance improvements, which can be masked by measurement errors and other uncertainties.

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**RNN Application**: An RNN could be valuable in this area. By training an RNN on data from flights with and without specific retrofits, the model could learn to isolate the effect of the retrofit on fuel consumption, even if the improvements are small. This could lead to more confident assessments of the effectiveness of different retrofits.

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**Data-Based Evaluation Methods:** The article discusses using machine learning models, like random forests, to simulate fuel flow and evaluate fuel economy67. It highlights the importance of data quality for these models.

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**RNN Application**: While the article focuses on random forests, an RNN could be a powerful alternative for modeling fuel flow. RNNs excel at capturing temporal dependencies, which are crucial for understanding how fuel consumption evolves throughout a flight. An RNN could potentially outperform other ML models in predicting fuel flow, particularly in scenarios with fluctuating flight conditions.

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**New Outcomes and Insights:** An RNN's capacity to learn complex patterns could potentially reveal new insights into the factors influencing fuel efficiency. This might involve identifying previously unknown correlations between flight parameters, weather conditions, and fuel consumption, or uncovering subtle ways in which retrofits impact fuel use under different operational conditions.

If our model were to have more features available such as in-flight changes of weather, engine performance, and exact route mileage, then we could produce an even more robust outcome for these resources to be chosen with a finer tooth comb, if you will.

**References**

Baumann, S., Neidhardt, T., & Klingauf, U. (2021). Evaluation of the aircraft fuel economy using advanced statistics and machine learning. *CEAS Aeronautical Journal*, *12*, 669–681. <https://doi.org/10.1007/s13272-021-00508-8>

Pre-Processing

Proper data pre-processing involves filtering out unnecessary features, handling missing or erroneous data, and transforming the dataset into a form that aligns with the goals of the analysis. This step is critical, as the quality of the input data significantly impacts the accuracy and reliability of the resulting model. In the context of our project, this preprocessing stage was a vital component of preparing the dataset for effective training and testing. The dataset obtained from the FAA’s TFMSC database provided us with a lot of information; however, it had some columns that were irrelevant to our model. It needed to be cleaned up by removing zero values from the departures as those were not necessary since we are focused on expanding the departures associated with each aircraft type at each airport during the time frame of September 21st, 2022, through October 1st, 2022. Once each of these departures had been expanded to create its own flight record of a departure, then we could start identifying the geographic distances, measured in Nautical Miles, between each of the 16 different airports. The airport’s nautical mileage is calculated using the geopy library in Python. It corresponds the distance from MCO (Orlando International Airport) to each of the respective airports in dataset. Once this data was calculated, I used the cost of Jet-A Fuel during that time frame, which was when Hurricane Ian hit Florida. Using these two columns, the fuel cost associated with each flight was able to be calculated as an important field for our model. The model will use the costs associated with the fuel to predict and choose what flight option, or resource in this context, is best suited for extracting the maximum number of people out of the impending impact zone whilst keeping fuel costs at a minimum. Moving into the dataset on the weather side….

A graph of a plane type

Description automatically generated

A screenshot of a graph

Description automatically generated