**Project Proposal**

“A Universal Model for Planning the Optimal Airline Fleet Size, Composition and Seat Configuration, using Advanced Analytics.”

By

**Seyed Roohollah Mousavi**

W1953084

M.Sc. Data Science and Analytics

Master Dissertation Proposal 2023

**University of Westminster**

Project supervisor

**Prof. Deepika Deepika**

# Introduction

The aviation industry is an ever-changing field that transports millions of passengers daily through networks of interconnected routes. As this industry progresses it faces a multitude of challenges including fluctuating fuel prices, shifting market demands, and geopolitical influences. At the core of these challenges lies a crucial question that every airline must confront; "Which aircraft and how many of each should we operate, and where should we fly them?"

The significance of this question stems from the vast investments involved. An airline's fleet consists of types of aircraft each with its capacity, range, and operational costs. The selection and allocation of these aircraft have far-reaching impacts on profitability, operational flexibility, customer satisfaction, and environmental impact. It's not about having planes; it's about having the right planes at the right time to serve the appropriate routes.

However, determining the fleet composition is not an easy task. It requires consideration of limitations, projected market demands, production lead times, aircraft-specific characteristics, fuel price predictions, environmental considerations, operational costs and profitability of different routes, etc.

This study aims to tackle this challenge by creating a model based on data, which airlines can use to determine the best fleet size and composition. Through the utilization of analytics, this research hopes to provide airlines with a tool to navigate their future in an increasingly competitive aviation industry.

# Background and Rationale

## Airline Fleet Planning

The importance of fleet planning for airlines cannot be overstated, considering its impact on an airline's operational efficiency, financial performance, and environmental sustainability. Several authors over the years have addressed various facets of fleet planning, emphasizing different objectives, constraints, and methodologies. This chapter presents a synthesis of significant contributions in this realm.

Historically, fleet planning was an intricate blend of art and science, often guided by market demand, aircraft availability, and economic factors. As the aviation industry matured, it soon became apparent that fleet decisions had cascading impacts, influencing not only the financial health of an airline but also its brand, operational flexibility, and growth potential. A misstep in fleet planning can lead to lost market opportunities or being saddled with inefficient aircraft that bleed resources.

## Financial Constraints and Market Forecasts

The airline industry is notorious for its volatile nature, with profitability affected by a multitude of external factors. Fuel prices, which account for up to 30% of an airline's operational costs (IATA Sustainability and Economics, 2023), are known for their unpredictability. Furthermore, geopolitical events, technological innovations, and global economic shifts can drastically alter market demands. Airlines, therefore, operate in a space where long-term commitments (like fleet acquisition) intersect with a constantly changing market landscape.

## Aircraft Production and Lead Times

Ordering new aircraft isn't as simple as placing an order and awaiting delivery. Aircraft manufacturers, like Airbus and Boeing, have backlogs spanning years. Airlines need to forecast their needs well in advance, considering the lead time for aircraft production. Moreover, customization choices – ranging from seating configurations to in-flight entertainment systems – add layers of complexity to this timeline.

## Fuel Consumption and Environmental Considerations

As the world grapples with the challenge of climate change, there's a growing emphasis on reducing carbon footprints across all sectors, including aviation. Modern aircraft designs focus on fuel efficiency, producing fewer emissions than older counterparts. Thus, fleet decisions today also echo in the environmental corridors, with airlines facing both regulatory pressures and a moral obligation to operate cleaner.

## The Digital Transformation

The advent of data science, machine learning, and artificial intelligence has transformed industries globally. In aviation, these tools offer a promise: the ability to make more informed, accurate, and timely decisions. While intuition and experience will always have their place, the potential to harness vast datasets and extract actionable insights from them is revolutionizing fleet planning processes.

## Literature Review

(New, 1975) and (Schick & Stroup, 1981) are among the pioneering researchers in airline fleet planning. They developed and applied linear programming models aiming to minimize the net present value of cash flows associated with aircraft operation. The primary decision variables in these models are the timing of aircraft investment and disposal, offering a chronological perspective on fleet management.

With rising environmental concerns and the airline industry's significant carbon footprint, researchers started to incorporate environmental objectives into fleet planning. (Khoo & Teoh, 2014) and (Rosskopf, Lehner, & Gollnick, 2014) are notable for presenting models that give weight to both economic and environmental objectives, marking a shift towards sustainability in airline fleet management.

Leasing aircraft can offer flexibility in managing fleet capacity, especially in an environment characterized by demand fluctuations. (Bazargan & Hartman, 2012) developed an extended fleet planning model, integrating aircraft leasing as a decision variable. On a related note, (Hsu, Li,, Liu, & Chao, 2011) explored the ramifications of demand volatility on the proportion of leased aircraft in an airline's fleet.

(Müller, Kieckhäfer, & Spengler, 2018) ventured into the intricate relationship between emission thresholds, retrofit options, and their subsequent pricing and savings. This work provides invaluable insights into retrofit decisions and their influence on fleet composition. Alongside fleet planning, associated decisions like fleet assignment and crew pairing have also been tackled. (Özener, Matoglu, Günes, Haouari, & Sözer, 2017) devised a comprehensive model that integrates fleet assignment with crew pairing, addressing both aspects in a unified framework.

Other researchers have brought to the fore enhanced revenue models in the context of fleet assignments. Cynthia Barnhart's work in 2009 titled "Airline Fleet Assignment with Enhanced Revenue Modeling" is a testament to this effort (Berhart, Farahat, & Lohatepanont, 2009). Moreover, (Clarke, Hane, Johnson, & Nemhauser, 1996) widened the scope of fleet assignments by incorporating maintenance and crew considerations, adding another layer of complexity to fleet planning models.

Holloway's contribution in 2008 introduced the concept of Demand-Driven Fleet Management (DFM) (Holloway, 2008). It emphasizes the flexibility that airlines must have to switch aircraft based on capacity requirements on or close to the day of operation, reflecting the dynamic nature of airline operations.

In recent years, Oliveira's works in 2021 and 2022 shed light on the link between energy intensity reduction and fleet modernization. He found that spikes in fuel prices can expedite the fleet rollover and modernization by approximately 3–4 years (Oliveira, Narcizo, Caliari, Morales, & Prado, 2021). Moreover, his 2022 study indicates that increasing energy costs might encourage greater fleet modernization in the long run, with airlines potentially aiming for more eco-efficient operations up to two years post a surge in fuel prices (Oliveira, Caliari, & Narcizo, An empirical model of fleet modernization: On the relationship between market concentration and innovation adoption by airlines, 2022).

Multiple-criteria decision-making (MCDM) methods have been used extensively throughout the literature since 2011. A cursory review of the extant literature reveals some noteworthy trends and points of contention. For instance, (Ozdemir, Basligil, & Karaca, 2011)utilized the Analytic Network Process in their comparison of aircrafts like A319, A320, and B737, considering factors like maintenance cost, reliability, and delivery time. This study, like others, centers its focus on cost, time, and physical attributes. Similarly, (Gomes, Fernandes, & Soares de Mello, 2012) took a novel approach with NAIADE Method for assessing aircraft types such as Cessna 208 and Beechcraft 1900, underlining financial, logistic, and quality factors. Notably, many of the studies, ranging from those of (Teoh & Khoo, 2015) to (Ardil, 2020), employ the Analytic Hierarchy Process among other methodologies to weigh the merits and demerits of various aircraft types against a set of established criteria.

However, a critical observation across these studies suggests some limitations. Primarily, the aircraft types processed are frequently restricted to a narrow range, often just a handful of models. This potentially limits the breadth of their findings. Furthermore, the historical data upon which these evaluations are based appears rather simplistic, not delving into intricate factors that might affect aircraft performance or long-term viability. Additionally, route considerations within these models are rather general, lacking specificity to particular routes or flight patterns.

With this in mind, there emerges a clear opportunity to utilize more advanced analytics, machine learning, and data science principles to bridge these gaps. Such an approach promises a more comprehensive evaluation of aircraft, accounting for intricate historical data, specific route considerations, and other nuanced factors that might influence aircraft selection. In conclusion, while the present body of literature offers valuable insights, there remains ample space for richer, more detailed investigations that tap into the potential of contemporary analytical tools.

# Research Question

At the core of this research lies the challenge of constructing an adaptive model for airlines that brings together the various components of fleet management: acquisition, lease, seating configuration and route profitability, under the lens of advanced analytics. From this central theme, the research seeks to address the following questions:

Main Research Question (RQ):

How can advanced analytics aid in creating a robust model to guide airlines in determining the optimal fleet size and composition, considering different financial and environmental constraints as well as different decisional criteria and probable phenomena indicators?

To delve deeper into the complexities of this overarching question, we outline the following sub-questions:

Sub-Question 1 (RQ2.1):

What are the primary decisional criteria that influence decisions in airlines, and how do these decisions affect long-term fleet composition and operational efficiency, and how these criteria can be quantified?

Sub-Question 2 (RQ2.2):

How do external market dynamics, such as fuel price variations and route demand fluctuations, affect the frequency and scale of these fleet planning scenarios?

Sub-Question 3 (RQ2.3):

How do trends in fleet modernization correlate with economic factors like energy cost changes, and what are the ensuing operational implications for airlines?

Sub-Question 4 (RQ2.4):

With the growing trend of aircraft leasing, how can analytics predict and guide leasing decisions, ensuring that they complement overall fleet management strategies?

Sub-Question 5 (RQ2.5):

Given the potential of Demand-Driven Fleet Management (DFM), how can real-time data analytics optimize fleet adjustments in response to immediate demand fluctuations?

These sub-questions are designed to holistically tackle the complexities of fleet management, ensuring that the final analytical model is both comprehensive and applicable in the current airline industry scenario.

This structure is meant to guide the research into deep-diving into each of these significant areas while maintaining the core focus on the application of advanced analytics.

# Research Methodology

## Data Collection

* Data Sources: Identify and compile datasets from aircraft manufacturers (like Airbus, Boeing), airline industry reports, market forecasts, and fuel price databases. Public databases, company annual reports, and industry-specific publications can be potential data sources.
* Data Quality: Ensure the quality of the collected data by checking for missing values, inconsistencies, or outliers. Implement data cleaning techniques as needed.

## Exploratory Data Analysis (EDA)

* Data Visualization: Use tools such as Python (with libraries like Matplotlib, Seaborn) or R to visualize the data. This will help understand underlying patterns, relationships, and potential outliers.
* Statistical Analysis: Employ statistical methods to describe data characteristics, distribution, and significant factors that might affect fleet decisions.

## Model Development

* Feature Engineering: Based on the EDA, select and engineer features that will act as input variables for the model. These can be direct data (like fuel price) or derived features (like average demand growth).
* Model Selection: Depending on the data nature and problem specifics, consider regression models, optimization models, or even machine learning algorithms. It might be beneficial to test multiple models to ascertain which provides the best recommendations.
* Model Training: Use a portion of the collected data to train the model, adjusting parameters and features to enhance its accuracy and reliability.

## Model Validation and Testing

* Splitting Data: Reserve a portion of the data (preferably more recent data) for model testing. This ensures the model isn't just fitting past data but can make accurate recommendations for near-future scenarios.
* Evaluation Metrics: Decide on metrics to evaluate model performance. These could be Mean Absolute Error, Root Mean Square Error, or custom metrics tailored to the project's specific requirements.

## Sensitivity Analysis

* Scenario Analysis: Given the uncertainties in the airline industry, it's essential to understand how sensitive the model's recommendations are to changes in input data. For example, how does the recommendation change if fuel prices increase by 10% or if a specific route's demand drops by 15%?

## Refinement and Iteration

* Based on model performance and sensitivity analysis, refine the model. Adjust features, parameters, or even consider alternative modeling approaches to improve outcomes.

## Documentation

* User Guide: Draft comprehensive documentation for the model, detailing its use, assumptions, and potential limitations. This ensures that the tool remains usable and adaptable by airlines or other stakeholders.

# Plan of Work and Time Schedule

## Phase 1: Data Collection (Weeks 1-3)

Week 1:

* Identify primary data sources for aircraft specifics, fuel prices, and market forecasts.
* Initiate communications with potential data providers or purchase datasets if necessary.

Week 2-3:

* Compile the gathered data into a centralized database or platform.
* Begin preliminary data quality checks, ensuring no significant gaps or inconsistencies.

## Phase 2: Exploratory Data Analysis (Weeks 4-6)

Week 4:

* Visualize data to recognize patterns, relationships, and potential outliers.
* Perform basic statistical analyses to understand data distributions and key metrics.

Week 5-6:

* Deeper dive into specific variables (like fuel price trends, aircraft production lead times).
* Document findings and insights that can influence the modeling phase.

## Phase 3: Model Development (Weeks 7-10)

Week 7:

* Initiate feature engineering based on insights from EDA.
* Decide on an initial model structure and approach.

Week 8-9:

* Train the initial model using a subset of the data.
* Adjust model parameters for optimal performance.

Week 10:

* Perform initial tests of the model's recommendations against known historical decisions.

## Phase 4: Model Validation and Testing (Weeks 11-13)

Week 11:

* Use reserved test data to validate the model's performance.
* Evaluate using predefined metrics (like MAE, RMSE).

Week 12:

* Refine the model based on validation results.
* Re-test refined model to ensure improvements.

Week 13:

* Begin sensitivity and scenario analysis to understand the model's robustness against various potential future scenarios.

## Phase 5: Refinement and Documentation (Weeks 14-16)

Week 14:

* Based on all previous findings, make final refinements to the model.

Week 15:

* Start drafting comprehensive documentation detailing the model's design, functionality, and application guidelines.

Week 16:

* Complete the documentation.
* Prepare for project submission, ensuring all components are in place and well-integrated.

# Bibliography

Özener, O. Ö., Matoglu, M. Ö., Günes, E., Haouari, M., & Sözer, H. (2017). Solving a large-scale integrated fleet assignment and crew pairing problem. *Annals of Operations Research*, 1-24.

Ardil, C. (2020). Trainer Aircraft Selection Using Preference Analysis for Reference Ideal Solution (PARIS). *International Journal of Aerospace and Mechanical Engineering,*.

Bazargan, M., & Hartman, J. (2012). Aircraft replacement strategy: model and analysis. *Journal of Air Transport Management*, 26-29.

Berhart, C., Farahat, A., & Lohatepanont, M. (2009). Airline Fleet Assignment with Enhanced Revenue Modeling. *Operations Research*, 231-244.

Clarke, L. W., Hane, C. A., Johnson, E. L., & Nemhauser, G. L. (1996). Maintenance and Crew Considerations in Fleet Assignment. *Transportation Science*, 249-260.

Gomes, L. F., Fernandes, J. E., & Soares de Mello, J. C. (2012). A fuzzy stochastic approach to the multicriteria selection of an aircraft for regional chartering. *Journal of Advanced Transportation*.

Holloway, S. (2008). *Straight and Level, Practical Airline Economis.* Hampshire, England; Burlington, USA: Ashgate Publishing.

Hsu, C. I., L. H., Liu, S. M., & Chao, C. C. (2011). Aircraft replacement scheduling: a dynamic programming approach. *Transportation Research Part E: Logistics and Transportation Review*, 41-60.

IATA Sustainability and Economics, S. G. (2023, 06). *IATA feul fact sheet.* Retrieved from IATA: https://www.iata.org/en/iata-repository/pressroom/fact-sheets/fact-sheet---fuel/

Khoo, H. L., & Teoh, L. E. (2014). A bi-objective dynamic programming approach for airline green fleet planning. *Transportation Research Part D: Transport and Environment*, 166-185.

Müller, C., Kieckhäfer, K., & Spengler, T. S. (2018). The influence of emission thresholds and retrofit options on airline fleet planning: An optimization approach. *Energy Policy*, 242-257.

New, C. C. (1975). TRANSPORT FLEET PLANNING FOR MULTI-PERIOD OPERATIONS. *Operational Research Quarterly*, 151-166.

Oliveira, A. V., Caliari, T., & Narcizo, R. R. (2022). An empirical model of fleet modernization: On the relationship between market concentration and innovation adoption by airlines. *Research in Transportation Business & Management*.

Oliveira, A. V., Narcizo, R. R., Caliari, T., Morales, M. A., & Prado, R. (2021). Estimating fuel-efficiency while accounting for dynamic fleet management: Testing the effects of fuel price signals and fleet rollover. *Transportation Research Part D: Transport and Environment*.

Ozdemir, M. S., Basligil, H., & Karaca, M. (2011). Aircraft Selection Using Analytic Network Process: A Case for Turkish Airlines. *Proceedings of the World Congress on Engineering*.

Rosskopf, M., Lehner, S., & Gollnick, V. (2014). Economic-environmental trade-offs in long-term airline fleet planning. *Journal of Air Transport Management*, 109-115.

Schick, G., & Stroup, J. (1981). Experience with a multi-year fleet planning model. *Omega*, 389-396.

Teoh, L. E., & Khoo, H. L. (2015). Airline Strategic Fleet Planning Framework. *Journal of the Eastern Asia Society for Transportation Studies*.