I. Introduction

This project aims to assist ABC Airlines in maximising the profits of its domestic flights. By creating a model that identifies the ideal combination of aircraft for each route, we can help the airline boost revenue while cutting costs. This real-world application provides valuable insights, such as determining that they needs seven Boeing 737s for the Denver to Newark route. It's all about leveraging their assets effectively!

The project revolves around the application of the **Fleet Assignment Problem (FAP)** within the context of airline operations, specifically targeting ABC Airlines. This problem involves assigning various types of aircraft to a set of routes in a manner that maximises profit while adhering to operational constraints.

The FAP can be modelled using Integer Linear Programming (ILP). In this formulation, we define decision variables that represent the number of each aircraft type assigned to specific routes. To ensure realistic and feasible solutions, several constraints must be incorporated into the model.

Using the PuLP library in Python, we can implement this ILP model. This powerful tool allows for the definition of the objective function and constraints, followed by solving the model to identify optimal fleet assignments based on real-world data. By applying operations research techniques, this project not only enhances the operational efficiency of ABC Airlines but also provides actionable insights for strategic decision-making.

I. Problem Description and Formulation

Our model is designed to account for all the recent changes affecting ABC Airlines, with the primary goal of maximising the company's profits. Mathematically, this involves optimising the value derived from the difference between total revenue and total costs. This relationship is encapsulated in our objective function, as detailed in Equation 1.

$$Maximize: Profit = Total\ Revenue - Total\ Costs \qquad (1)$$

To maximise profit effectively, we need to consider various factors, commonly referred to as constraints. Let’s explore each of these constraints one by one.

The first constraint we need to consider is quite straightforward but crucial for our model's effectiveness. Essentially, this rule states that an aircraft cannot operate a route that starts and ends at the same airport. For instance, it wouldn't make sense for a plane to fly from Denver to Denver, as that wouldn't provide any value for United Airlines. This constraint is represented by Equation 2.

$$Route_{ij} = 0 \tag{2}$$

Where I and J are airports and I$=J$

The second constraint ensures passenger demand gets met on every route.
Simply put: total seats across all flights between any two airports must equal or exceed that route's demand. Equation 3 captures this requirement.

$$\sum (S_i * X_{ijk}) \geq Route_{ij} \tag{3}$$

Where X is the total number of planes of a certain type
X is total planes of a given type
I and J are airports

Our third constraint tackles aircraft utilization limits. Each plane maxes out at 20 hours of daily flight time, leaving four hours for essential ground operations—refueling, passenger boarding, and turnaround preparations.

The math is straightforward: total available flight hours across all aircraft on a route must match or exceed the route's flight duration multiplied by required daily frequency. This prevents our model from creating impossible schedules that ignore real-world operational demands.

Constraint 3 appears in equation 4.

$$20 * \sum X_{ijk} \geq F_{ij} * A_{ij} \tag{4}$$

Where X is the total number of planes of a certain type
F is the required daily frequency of flights
A is the flight time for that route

Flight frequency represents another critical constraint—each route requires a minimum number of daily flights to serve diverse passenger preferences. Take Chicago-Newark, United's highest-demand corridor: some travelers need morning departures while others prefer evening slots.

This constraint ensures our aircraft deployment creates adequate scheduling options across different time windows, preventing the model from consolidating all capacity into a single daily flight. The requirement forces realistic service frequency that matches passenger booking patterns.

Constraint 4 appears in equation 5.

$$\sum X_{ijk} \geq F_{ij} \tag{5}$$

Where X is the total number of planes of a certain type
F is the required daily frequency of flights

The final constraint addresses fleet capacity limits—seemingly obvious but operationally crucial. United can't deploy more aircraft than they actually own. If their fleet includes 48 Boeing 787s, route assignments cannot exceed this physical inventory.

This restriction prevents the model from generating theoretical solutions that ignore real-world asset limitations. Without this constraint, optimization could recommend impossible deployments that exceed actual fleet size.

Constraint 5 appears in equation 6.

$$X_{ijk} \leq C \tag{6}$$

Where X is the total number of planes of a certain type
C represents a constant of maximum plane availability

III. Numerical Implementation and Results

Given ABC massive scale, we narrowed our optimization scope to domestic operations only. Initially targeting all 238 domestic destinations proved unrealistic within project constraints, so we concentrated on United's seven major hubs.

This hub-focused approach generated 42 unique route combinations—each hub connecting to the other six (7 × 6 = 42). Our selected hubs include:

- Denver (DEN)
- Chicago (ORD)
- Newark (EWR)
- Washington (IAD)

- San Francisco (SFO)
- Los Angeles (LAX)
- Houston (IAH)

The domestic fleet consists of five aircraft types:

- Boeing 787
- Boeing 777
- Boeing 767
- Boeing 737
- Airbus 320

All aircraft possess sufficient range to complete direct flights between any hub pair without intermediate stops.

After organizing our data arrays in PuLP, we defined the optimization variables as X. Each X variable represents a specific aircraft assignment to a particular route.

Our variable structure uses three indices: i (departure airport), j (destination airport), and k (aircraft type). This three-dimensional approach captures every possible combination of route and equipment assignment within our optimization framework.

Equation 7 presents the complete variable description.

$$X_{ijk} \tag{7}$$

Where i is the starting airport
j is the destination airport
k is the type of plane used.

In practical terms, each route generates five variables—one for every aircraft type in United's domestic fleet. Our complete model therefore contains 210 total variables (42 routes × 5 aircraft types).

After implementing our objective function and constraints as discussed, we executed the optimization model. The solution yielded an optimal profit of $2,722,859, with detailed aircraft allocations presented in Table below.

	Optimized Values
Profit	$2 722 859
Number of Boeing 737	136 planes
Number of Boeing 767	38 planes
Number of Boeing 777	0 planes
Number of Boeing 787	41 planes
Number of Airbus 320	97 planes

These results align with our expectations—the substantial aircraft requirements reflect the high passenger volumes across hub routes. While the $2.7 million profit appears significant, it represents a conservative estimate since our model only accounts for direct flight operations costs, excluding broader corporate expenses like overhead, marketing, and ground infrastructure.

IV. Conclusion

Airlines' domestic profitability through strategic fleet deployment. By focusing on hub-to-hub operations and balancing aircraft utilization against demand patterns, the model generates actionable insights that could improve revenue by $2.7 million while maintaining operational feasibility. The constraints we've implemented—from demand fulfillment to aircraft availability—mirror real-world operational challenges, making our recommendations immediately applicable. As the aviation industry continues recovering from pandemic disruptions, data-driven fleet optimization becomes essential for survival. This model provides United with a robust foundation for making informed capacity decisions that maximize both customer satisfaction and financial performance across their core domestic network.