AIRLINE FLEET MANAGEMENT WITH LEASING AND AIRCRAFT CONVERSION: A MIXED-INTEGER PROGRAMMING APPROACH

MIAO ZHOU

MPhil

The Hong Kong Polytechnic University

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The Hong Kong Polytechnic University

Department of Aeronautical and Aviation Engineering

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Miao Zhou

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CERTIFICATE OF ORIGINALITY

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Abstract

Fleet management is a cornerstone of airline operations, influencing long-term profitability, environmental sustainability, and operational efficiency. This thesis addresses the complex challenges airlines face in managing diverse fleets, particularly in the context of fluctuating passenger and cargo demands, aging aircraft, and the growing importance of sustainable aviation practices. We develop a mixed-integer stochastic programming model to optimize fleet management decisions, including aircraft purchases, leasing options, and the conversion of passenger aircraft to freighters (P2F). Through extensive numerical experiments and sensitivity analyses, we demonstrate that operating leases offer flexibility in meeting demand while reducing financial risk and enabling airlines to adopt more environmentally friendly policies. In contrast, purchasing and capital leases enhance long-term profitability but increase debt risk. P2F conversions emerge as a viable strategy to reduce future liabilities and accommodate rising cargo demand driven by e-commerce growth, though they may lead to higher emissions for airlines. Our findings provide actionable insights for policymakers, highlighting the need for strategic fleet management that balances financial prudence, operational flexibility, and environmental sustainability. We recommend policy measures such as tax incentives for leasing, streamlined certification for P2F conversions, and subsidies for fleet modernization to support airlines in achieving both economic and environmental goals. This study contributes to the ongoing discourse on sustainable aviation by offering a comprehensive framework for fleet management that aligns with global climate objectives and economic resilience.

Publications Arising from the Thesis

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Chapter 1

Introduction

Fleet management is a critical component of long-term strategic decision-making in the aviation industry. A study by Wang (2015) demonstrated that fleet management involves a strategic decision-making process that typically requires planning in advance, aligning fleet size and structure with forecasted demand to optimize operational efficiency and profitability under competitive market conditions. Similarly, Belobaba et al. (2015) highlighted that aircraft fleet management is an essential part of an airline's overall operating plan.

As fleet management is a strategic decision for airlines, it must consider various factors. Belobaba et al. (2015) pointed out that these considerations include the airline's goals and objectives, passenger and cargo demand, the impact of service patterns on market share, and airplane performance, among others. Moreover, with emerging challenges and new technologies, the factors influencing fleet management have evolved significantly. These developments not only offer new opportunities but also pose additional challenges for fleet management.

According to the global fleet development forecast for 2023–2042 (The Boeing Company, 2024), global passenger traffic is projected to grow at an average annual rate of 4.7%. This growth is attributed to rising GDP and population, which make air travel increasingly attractive, thereby increasing demand for passenger aircraft. Similarly, air cargo traffic is expected to grow by 4% annually through 2043, driven by the expanding role of e-commerce and the growth of express networks in emerging markets. For example, Figure 1.1 illustrates Cathay Pacific's cargo volume and cargo profit data from 2013 to 2022 (Cathay Pacific, 2022). Notably, Cathay Pacific observed an upward trend in cargo profit even during the COVID-19 crisis. With the impact of COVID-19 now behind us, global air cargo traffic is expected to double over the next two decades (The Boeing Company, 2024).

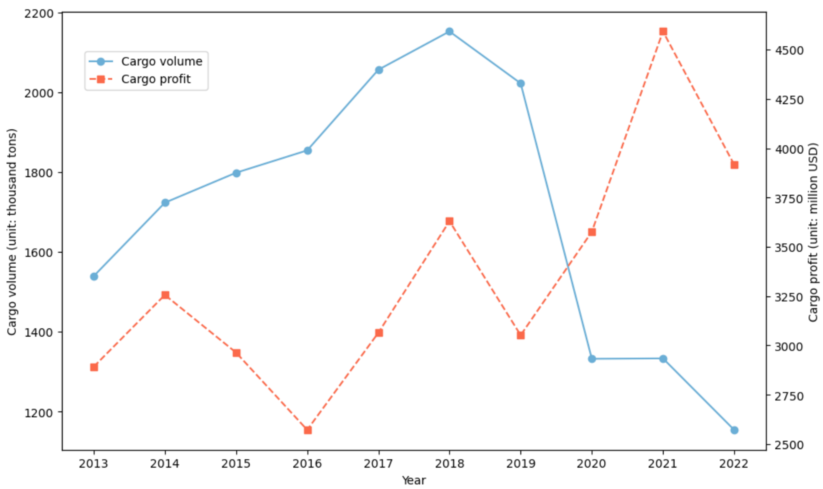

Figure 1.1: Cargo Volume and Cargo Profit of Cathay Pacific from 2013 to 2022.

To address the growing demand for both passenger and cargo services, airlines have multiple fleet management options. One primary option is purchasing aircraft. Clark (2017) emphasizes the important role of purchasing aircraft in fleet planning. Owning aircraft allows airlines to have complete control over their fleet, offering long-term cost benefits. Another key fleet management option is leasing, which offers airlines flexibility with lower initial capital requirements. Several studies emphasize the growing importance of leasing in fleet management. Bourjade et al. (2017) examined the impact of leasing on marginal returns and airline profitability under different operating models using a linear regression model. Wandelt et al. (2023) highlighted the leasing industry's significant role in airline operations, noting that the share of leased aircraft increased from less than 5% in the 1980s to nearly 50% during the COVID-19. Furthermore, Bourjade and Muller-Vibes (2023) confirmed the strategic role of leasing in enhancing operational efficiency, using a stochastic frontier approach.

As cargo operations become increasingly vital to the airline industry, airlines are utilizing both dedicated freighters and the belly space of passenger aircraft for cargo transportation. According to Fung et al. (2005), between 55% and 60% of cargo at Hong Kong International Airport is transported in the belly compartments of passenger aircraft. This information provides valuable insights into the dynamics of cargo transportation.

The conversion of P2F holds significant market potential, driven by the rapid growth of e-commerce and the need for fleet renewal. It is estimated that 20,555 aircraft will be retired globally between 2023 and 2043 (The Boeing Company, 2024). The global P2F conversion market was valued at USD 2.14 billion in 2021 and is projected to grow from USD 2.52 billion in 2022 to USD 5.19 billion by 2029, reflecting a robust compound annual growth rate of 10.84% during the forecast period from Fortune Business Insights (2024). In terms of aircraft selection for P2F, the market is divided into narrow-body, wide-body, and regional jets. Both narrow-body and wide-body aircraft have their respective advantages: narrow-body aircraft offer high versatility for e-commerce applications, while wide-body aircraft provide excellent cargo-carrying capabilities when converted into freighters.

While fast growth in demand presents significant operational challenges to the air transport industry, it also brings forth substantial adverse environmental impacts. As noted by Lee et al. (2021), global aviation operations contribute to anthropogenic climate change via a complex set of processes that lead to a net surface warming, including both CO_2 and non-CO_2 effects. With growing attention to environmental factors, airlines are increasingly integrating sustainability policies into their fleet management strategies. As illustrated in Amankwah-Amoah (2020), this includes a critical shift towards optimizing for reduced carbon footprint, enhanced fuel efficiency, and lower noise pollution. Under the influence of evolving environmental policies, fleet management has become more critical than ever, as it directly impacts both the company's revenue management and its corporate social responsibility.

Considering the importance of airline fleet management, many researchers have developed optimization models to address airline fleet management. However, studies considering multiple airline acquisition methods tend to overlook the impact of uncertainty, while research incorporating uncertainty into airline strategic planning often lacks comprehensive consideration of various aircraft types, the diversity of aircraft acquisition methods, and the impact of environmental policies and airline financial health. There is a compelling need to revisit and modernize long-term fleet-planning methodology to reflect current market realities.

In light of the changing dynamics in both the passenger and cargo markets within the aviation industry, our research focuses on developing a mixed integer stochastic programming model for airline fleet management. Throughout the modeling process, we have considered the operations of both passenger aircraft and freighters, incorporating not only passenger demand but also cargo demand. We have bridged these two distinct aircraft types through the business of passenger-to-freighter (P2F) conversion. Additionally, we examine various strategies for aircraft acquisition, including aircraft purchases, capital leases, and operating leases. A key feature of our approach is the explicit incorporation of uncertainty into the modeling process. Our model captures uncertainties related to future passenger and cargo demand, fuel price, discount rate and environmental cost, thus enabling a robust evaluation of different fleet management strategies. The proposed framework is designed to provide decision-making support for airlines of different scales under various future scenarios and expectations. Our analysis reveals that operating leases play a critical role in fleet acquisition, and that P2F conversions are particularly valuable for meeting growing cargo demand while maintaining a healthy debt level; however, they may also impose additional environmental costs on airlines.

It is important to note that fleet management operates at a higher strategic tier, as illustrated in Cynthia Barnhart (2003), providing a foundation for long-term capacity planning and capital allocation, whereas network planning and scheduling typically involve tactical or operational adjustments based on the available fleet. By emphasizing strategic fleet decisions, our model enables airlines to proactively respond to evolving market and regulatory conditions, rather than merely adapting existing routes and schedules.

The main contributions of this study are as follows:

1. We present a novel and comprehensive framework that integrates airline

decision-making on aircraft purchases, leases (both capital and operating), and P2F conversions within a unified model. A key innovation of our study is the explicit incorporation of multiple sources of uncertainty, such as demand, fuel price, and policy parameters, directly into the modeling process.

2. We develop a mixed integer stochastic programming model that systematically accounts for these uncertainties by generating and evaluating a rich set of future scenarios. We rigorously prove the computational complexity of the problem and validate the scientific soundness and practical feasibility of our approach through extensive computational experiments.

3. We perform detailed sensitivity analyses on budget constraints, maximum allowable unpaid debt, environmental cost, and projected trends in future passenger and cargo demand for different types of airlines. These scenario-based analyses yield actionable managerial insights for improving airline fleet management under various real-world uncertainties.

In the following, we review the existing literature on fleet management in Section 2. In Section 3, we explain our problem of fleet management. We formulate the problem of fleet management as a mathematical model in Section 4. Description of complexity of fleet management and a solving methodology are introduced in Section 5. The computational results and policy implications are shown in Section 6. Finally, we conclude and discuss the avenues for future studies in Section 7.

Chapter 2

Literature Review

This thesis is related to four streams of literature. The first body of relevant literature concerns fleet management, where various operations research methods have been utilized to optimize airline fleet management decisions. Initially, most researchers focused on building deterministic operations research models. Over time, the scope of factors considered in fleet management research has evolved, with early studies emphasizing simpler variables and later research incorporating more complex and dynamic elements. For example, Bazargan and Hartman (2012) optimized fleet size by developing an integer programming model to achieve the goal of replacing a portion of an airline's fleet. However, the model did not account for the impact of debt on airline operations or the different forms of aircraft leasing. In contrast, Hsu et al. (2013) and Chen et al. (2018) extended this research by considering both aircraft purchasing and multiple forms of leasing. However, they did not consider the impact of different aircraft models on airline operations. These studies failed to account for the simultaneous impact of passenger and cargo demand on fleet operations, the residual value of remaining aircraft at the end of the decision phase or the emerging technologies such as P2F conversions. Also, these studies fail to consider the impact of financial condition on the fleet management, such as the maximum unpaid debt and the uncertainty of discount rate.

Uncertainty poses a significant challenge in airline strategic planning, profoundly affecting decisions related to fleet management, route optimization, and resource allocation. As emphasized by de Wit (2022), robust policies were essential to address uncertainty in airline strategic planning. To tackle this issue, researchers adopted advanced methodologies, such as stochastic programming and multi-stage planning, to enhance decision-making under uncertainty. For example, Hsu et al. (2011) developed a stochastic dynamic programming model to optimize aircraft purchasing and leasing decisions by incorporating demand uncertainty. Likewise, Repko and Santos (2017) employed a scenario tree approach to address fleet management and assignment problems concurrently. However, these studies often neglected interrelated factors, such as fuel price volatility or regulatory policy changes. Furthermore, works by Khoo and Teoh (2014), Carreira et al. (2017), and Serrano-Hernandez et al. (2020) proposed stochastic models to optimize fleet composition under uncertain demand, but they failed to consider the impact of environmental policies on airline fleet management decisions and were limited to studies on a single type of airline. These limitations underscored the need for integrated models that holistically accounted for multifaceted uncertainties, paving the way for comprehensive research to bridge this gap and provide valuable managerial insights for developing robust policies in airline strategic planning.

The second stream of literature examines the role of freighters in airline operations and the optimization of cargo services. For instance, Budd and Ison (2017) analyzed the quantity and composition of dedicated freighter aircraft in global airfreight services, but their study overlooked the effects of dynamic demand environments or financial market fluctuations. Similarly, Baxter et al. (2018) used the case of Qantas Freight to underscore the critical role of freighters and the distinctiveness of freighter networks compared to passenger-aircraft networks, yet their analysis did not include specific mathematical models to substantiate the findings. In contrast, He et al. (2019) developed a three-stage stochastic programming model to optimize freighter revenue management, while B. Feng et al. (2020) addressed the air cargo forwarder selection problem through a two-stage distributionally robust optimization model. Nevertheless, these studies neglected to balance cargo and passenger demand within their frameworks and did not consider the influence of environmental policies on freighter management. Similarly, Gong et al. (2022) introduced demand uncertainty into the fleet sizing and pricing optimization problem. Although the study incorporated a unified formulation for satisfying both passenger and cargo demand, it failed to address the detailed fleet management problem. While it considered the usage of convertible aircraft, it did not account for the application of P2F conversion technology and neglected the impact of environmental policy. Collectively, these works either lacked rigorous quantitative experiments to validate their models across diverse real-world scenarios or underestimated potential synergies in fleet planning for different types of airlines and the broader implications of environmental regulations.

The third stream of literature explores the influence of Passenger-to-Freighter (P2F) conversions on airline fleet management. For example, Berlowitz (2014) investigated the technical feasibility of P2F conversions, focusing on engineering challenges, certification requirements, and operational modifications, but did not integrate these insights into a broader strategic fleet optimization framework. Similarly, L. Zhang et al. (2018) analyzed economic drivers behind P2F adoption, highlighting China's abundant stock of narrow-body passenger aircraft as ideal candidates for conversion, potentially enabling domestic self-sufficiency in standard-body freighters. However, their study relied on descriptive analysis and did not develop a quantitative optimization model to evaluate fleet-level decision trade-offs. Moreover, Baxter (2021) emphasized the growing dominance of P2F aircraft in global air cargo supply chains, noting that airlines increasingly retire aging factory-built freighters in favor of converted aircraft to improve fuel efficiency and reduce emissions intensity. Despite these observations, the study did not embed P2F conversion timing or scale within a formal fleet planning model. Additionally, Zheng et al. (2024) developed an economic equilibrium model to assess the dual-market impact of P2F conversions on passenger and cargo segments, incorporating competitive dynamics and government subsidies. While insightful, their approach remained at the market level and did not incorporate P2F decisions into an airline-specific optimization framework that jointly manages passenger aircraft, dedicated freighters, and convertible assets. Although H. Zhang and Chang (2025) developed a cross-border route optimization model for dispatching all-cargo and passenger-to-freighter aircraft, the study focused primarily on cargo network design and revenue maximization, without examining the integrated operational and financial effects of co-managing P2F aircraft alongside passenger and factory-built freighters within a single airline's fleet. Although these studies illuminated the technical viability, economic rationale, and market implications of P2F conversions, they consistently failed to incorporate P2F strategies as actionable decision variables within comprehensive airline fleet management models.

As a result, they provide limited guidance on optimal fleet management decision involving P2F conversion. This gap restricts the ability to quantify the long-term value of P2F flexibility in enhancing fleet adaptability, residual value, and sustainability performance across diverse airline business models.

The fourth stream of literature investigates the influence of environmental policy on airline fleet management, explicitly linking operational decisions to sustainability goals. As noted by Calvet (2024), sustainable aviation was critical to airlines' long-term planning, necessitating alignment of fleet management with environmental objectives. Early work by Brueckner and Zhang (2010) theoretically modeled the impact of airline emissions charges on airfares and network structure choices using an economics-based approach. Additionally, research addressed fleet management from an environmental sustainability perspective. For instance, Tsai et al. (2012) incorporated aircraft emission penalties into the objective function of an optimization model within the European Union Emissions Trading Scheme, while Müller et al. (2018) introduced CO_2 emission constraints to ensure compliance with carbon-neutral growth targets. More recently, Mitici et al. (2022) addressed operational challenges for short-range flights operated with electric aircraft through a two-stage mixed-integer programming model. Similarly, Justin et al. (2022) investigated the impact of introducing electric aircraft on regional air mobility by developing a mixed-integer programming model. Nonetheless, these optimization models addressing environmental policies often did not consider the differential impacts of such policies on airlines of varying scales. Moreover, they rarely accounted for uncertainty factors, such as demand volatility or fuel price fluctuations, thereby reducing their models' robustness in real-world scenarios.

In conclusion, while the existing literature has advanced mathematical models for airline fleet management, there still exists significant gaps. First, there is a lack of comprehensive models that integrate multiple sources of uncertainty. Second, prior research has largely overlooked the strategic implications of P2F conversions for fleet management, particularly how this technology enables the repurposing of aging passenger aircraft to enhance freight capacity and financial viability under uncertain conditions. Third, there is insufficient provision of managerial insights tailored to different airline types regarding optimal fleet management policies in volatile environments. This thesis addresses these shortcomings by developing a multi-stage stochastic optimization framework that incorporates divergent passenger and cargo demand trends, diverse uncertain parameters, and P2F technology adoption. Through this approach, we evaluate how P2F influences strategies for managing aging aircraft, accounting for financial constraints and environmental policies, and derive targeted managerial insights to guide resilient decision makings across airline archetypes.

Chapter 3

Problem Description

Consider a problem where an airline manages its fleet over a specified time horizon, which is divided into two interconnected phases: the decision phase and the extended phase. Figure 3.1 illustrates these phases and their relationship. In the decision phase, the airline can actively adjust its fleet size and composition by engaging in leases, purchases, P2F conversions, aircraft sales, or decommissioning. During this phase, the airline must not only ensure that its fleet meets passenger and cargo demand in the current period, but also strategically plan the composition and size of the fleet to be carried forward.

However, it is important to note that, in practice, airlines may continue to adjust their fleet size beyond the initial decision phase by purchasing or selling aircraft. The reason we do not consider such fleet size changes in the extended phase of our study is that this phase is specifically designed to evaluate the value of decisions made in the decision phase under uncertainty. To account for uncertainties such as demand fluctuations and fuel price volatility, we incorporate uncertainty parameters into the extended phase, thereby formulating the problem as a stochastic programming model. This approach yields more robust solutions, allowing for the evaluation of the effectiveness and long-term implications of earlier fleet decisions, particularly regarding the residual value and operational adequacy of the remaining fleet. The two-phase structure can be found in real-world planning. The decision phase corresponds to the near-term commitment window, where information is sufficiently reliable. Consequently, we do not incorporate uncertain parameters into our optimization model during this phase. In contrast, the extended phase represents a longer-term time horizon, where the lack of reliable information necessitates the inclusion of uncertainty in the optimization model to derive a robust policy.

This two-phase structure ensures that fleet planning decisions are forward-looking and robust, as the choices made in the decision phase directly determine the airline's operational capabilities and flexibility in the extended phase.

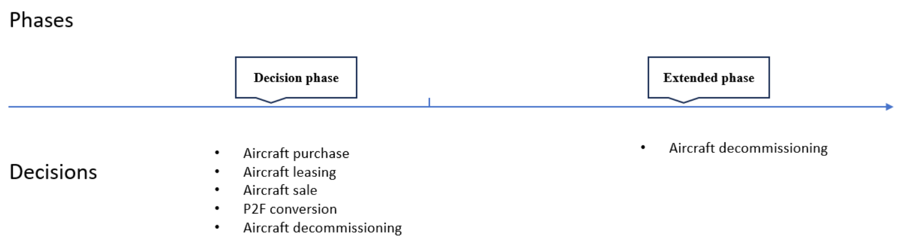

Figure 3.1: Different Types of Phases in the Model.

In our model, we use set $\mathcal{J}$ to represent the set of periods. Each period typically represents a year. To express it more accurately, we divide the set $\mathcal{J}$ into two subsets $\mathcal{J}_1$ and $\mathcal{J}_2$. We have $\mathcal{J}_1 \cup \mathcal{J}_2 = \mathcal{J}$, in which $\mathcal{J}_1$ represents the decision phase and $\mathcal{J}_2$ the extended phase. In this case, $\mathcal{J}_1 = \{0, 1, 2, 3, ...\overline{J}_1\}$ where $\overline{J}_1$ represents the last period of decision phase of the optimization problem, and $\mathcal{J}_2 = \{\overline{J}_1 + 1, \overline{J}_1 + 2, ...\overline{J}_2\}$ where $\overline{J}_2$ represents the last period of extended phase of the optimization problem.

3.1 Aircraft

In our model, we primarily consider three categories of aircraft. We represent the types of aircraft using the set $\mathcal{K}$. Specifically, we use $\mathcal{K}_1$ to represent the subset of passenger-aircraft types, $\mathcal{K}_2$ the subset of freighter types, and $\mathcal{K}_3$ the subset of converted freighter types. We assume that converted freighters can only be obtained through the conversions of certain models of passenger-aircraft. To simplify the model representation, we establish mutually exclusive sets $\mathcal{K}_1$, $\mathcal{K}_2$, and $\mathcal{K}_3$. Additionally, we assume a one-to-one invertible function f between the types of passenger-aircraft and freighters converted from the passenger-aircraft, that is, $\forall m \in \mathcal{K}_3, \exists n \in \mathcal{K}_1 : m = f(n)$. We use the set $\mathcal{I}_k$ to represent the ages of type k, and it is defined as $\mathcal{I}_k = \{0, 1, 2, 3, ..., \overline{I}_k\}$, where $\overline{I}_k$ is the maximum service age of type-k aircraft. To incorporate uncertainty into our optimization model, we use the set $\mathcal{S}$ to represent the set of scenarios employed in our study. To generate scenarios $s \in \mathcal{S}$, we assume that the annual rates of change for key parameters, including customer demand, cargo demand, oil prices, and discount rates in the extended planning phase follow a normal distribution, which capture the variability and risk in future market conditions, enabling robust optimization results.

In our research, we introduce the parameters $\rho_{i,k}(j)$ and $\sigma_{i,k}(j)$, which represent respectively the number of type-k aircraft of age-i available for use and the number of type-k aircraft of age-i owned by the airline due to the decisions made prior to the decision phase. These parameters directly influence the fleet size of the decision phase in the modeling process.

In our study, we specify several ways to acquire passenger-aircraft and freighters. Passenger-aircraft can be obtained through purchases, capital leases, or operating leases by the airline. After choosing the first two acquisition methods, we assume that the airline can obtain full ownership of the aircraft. We use parameter θ to measure the time to repay the principal and interest for purchasing aircraft. In our study, we assume that $\theta \geq 2$. We introduce the parameter γ to simulate the period during which the airline is unable to acquire aircraft through purchases, reflecting the lead time required for aircraft delivery. Specifically, in periods $j \in [0, \gamma - 1]$, the airline cannot acquire newly purchased aircraft; only from period γ onward do these aircraft become available for operation. This approach is intended to capture the practical scenario where airlines place purchase orders but must wait for delivery before integrating new aircraft into their fleet. Since delivery lead times vary across different aircraft types, our use of a single parameter γ serves as a simplified modeling strategy to represent this delay in a tractable manner. As for leasing aircraft, we use set $\mathcal{N}_{i,k}$ to represent the leased-in periods for type-k aircraft of age i. For the aircraft under operating lease, we use $\mathcal{N}^o_{i,k} = \{\underline{N}^o_{i,k}, \underline{N}^o_{i,k}+1, ..., \overline{N}^o_{i,k}\}$ to represent aircraft operating-leasing periods, where $\underline{N}^o_{i,k}$ and $\overline{N}^o_{i,k}$ are the minimum and the maximum lease duration for operating-leasing aircraft by the airline respectively. For the aircraft under capital lease, we use $\mathcal{N}^c_{i,k} = \{\underline{N}^c_{i,k}, \underline{N}^c_{i,k}+1, ..., \overline{N}^c_{i,k}\}$ to represent capital lease periods for type-k aircraft of age i, where $\underline{N}^c_{i,k}$ and $\overline{N}^c_{i,k}$ are the minimum and the maximum lease duration for aircraft under capital lease by the airline respectively. In our study, we set the parameters $\overline{N}^{o}_{i,k}$ and $\overline{N}^{c}_{i,k}$ as $\overline{I}_k - i$, which represents that the maximum lease duration is equal to its remaining service life, which is captured by the difference between $\overline{I}_k$ and i. To represent the costs incurred by the airline for purchasing and aircraft conversion at different time periods, we introduce the set $\mathcal{O}$ to represent the payment periods, $\mathcal{O}$ is defined as $\{0, 1, 2, ..., \theta - 1\}$. Additionally, we assume that the airline has full ownership of aircraft after completing the payment of the capital leases and cannot terminate the lease or purchase agreement because the termination cost of lease or purchase agreement is extremely high.

3.1.1 Purchase Expenses and Aircraft Conversion Expenses

We first introduce the formula for the equal principal repayment of purchasing aircraft, which includes both the principal and interest payments per period. We introduce the parameter $P_{i,k}(o)$ as the amount of money that needs to be paid at time o during the purchase cycle for a type-k aircraft of age i, $L_{i,k}$ as the monetary value of the aircraft, and α^p as the loan interest rate for the equal principal repayment per period for purchasing per aircraft. We use parameter ζ to represent the initial payment rate for purchasing aircraft. Equations (3.1)–(3.2) provide the formula for equal principal repayments, where the airline repays the same amount of principal in each period and pays interest on the remaining principal amount generated in that period. Equations (3.1) provide the formula for calculating the initial payment amount required by airline when purchasing an aircraft. The first term of equations (3.2) represents the equal principal payments whereas the second term represents the interest generated from the remaining principal.

$$P_{i,k}(o) = \zeta L_{i,k} \qquad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, o \in \mathcal{O} : o = 0, \tag{3.1}$$

$$P_{i,k}(o) = \frac{1}{\theta - 1}(1-\zeta)L_{i,k} + \alpha^p(1-\zeta)L_{i,k}\frac{\theta - o}{\theta - 1}$$
$$\forall k \in \mathcal{K}, i \in \mathcal{I}_k, o \in \mathcal{O} : 1 \leq o \leq \theta - 1. \tag{3.2}$$

For the cost of converting aircraft, we use the same calculation formula as for purchasing aircraft. We introduce the parameter $A_{i,k}(o)$ as the amount of money that needs to be paid at time o for a type-k passenger-aircraft of age i converted to a freighter, $A_{i,k}$ as the total expense of conversion and α^c as the loan interest rate for the equal principal repayment per period for converting per passenger-aircraft. Equations (3.3)–(3.4) provide the formula for calculating the expense paid in each period to convert a passenger-aircraft.

$$A_{i,k}(o) = \zeta A_{i,k} \qquad \forall k \in \mathcal{K}_1, i \in \mathcal{I}_k, o \in \mathcal{O} : o = 0, \tag{3.3}$$

$$A_{i,k}(o) = \frac{1}{\theta - 1}(1-\zeta)A_{i,k} + \alpha^c(1-\zeta)A_{i,k}\frac{\theta - o}{\theta - 1}$$
$$\forall k \in \mathcal{K}_1, i \in \mathcal{I}_k, o \in \mathcal{O} : 1 \leq o \leq \theta - 1. \tag{3.4}$$

3.1.2 Monetary Value of Aircraft

In this study, we assume that the airline depreciates its aircraft using the straight-line depreciation method, as demonstrated in Chen et al. (2018). We use parameter η to measure the residual value ratio of an aircraft. In our model, we assume that converting passenger aircraft into freighters does not increase the monetary value of the aircraft. Therefore, Equations (3.5) specifically provide the formula for calculating the initial monetary value of the freighters converted from passenger aircraft. Equations (3.6) provide the formula for calculating the monetary value of a type-k aircraft of age i.

$$L_{0,k} = L_{0,k'} \qquad \forall k \in \mathcal{K} : k \in \mathcal{K}_3, k' \in \mathcal{K}_1 : f(k') = k, \tag{3.5}$$

$$L_{i,k} = L_{0,k} - \tfrac{i}{I_k}(1-\eta)L_{0,k} \qquad \forall k \in \mathcal{K} : k \in \mathcal{K}, i \in \mathcal{I}_k. \tag{3.6}$$

3.1.3 Aircraft Maintenance Costs

In this study, we use the parameter E_i^k to represent the aircraft maintenance costs. As suggested by Sperry (2000), a strong linear relationship exists between aircraft age and maintenance cost. Accordingly, we assume that the variable E_i^k is only related to the aircraft's age i and aircraft's type k and follows a linear relationship. We introduce parameter υ_k to measure the annual increase in maintenance cost. Equations (3.7) provide the formula for calculating the maintenance costs of type-k aircraft of age i.

$$E_i^k = E_0^k + \upsilon_k i \qquad \forall k \in \mathcal{K}, i \in \mathcal{I}_k. \tag{3.7}$$

3.1.4 Aircraft Operating Costs

In this study, we define $F_{i,k,s}(j)$ as the operating costs for an age-i aircraft of type k in period j under scenario s. This total cost comprises two main components: the fuel cost, $F^1_{i,k,s}(j)$, and the environmental cost, $F^2_{i,k}(j)$. During the decision phase, the operating costs are primarily derived from historical airline data and are treated as deterministic parameters, denoted by $\bar{F}_{i,k}(j)$. The parameter $C^f_{i,k}$ represents the fuel consumption of an aircraft of type k at age i, while $\bar{\xi}(j)$ denotes the environmental cost associated with emissions due to environmental policy. According to Hassan et al. (2021), fuel consumption $C^f_{i,k}$ depends on both the aircraft type and its age, with older aircraft typically exhibiting reduced fuel efficiency and higher fuel consumption. Equations (3.8) provide the formulas for calculating the operating costs during the decision phase, while equations (3.9) present the formulas for computing the environmental cost for age i aircraft of type k at period j.

In the extended phase, we explicitly consider the uncertainty of the fuel cost $F^1_{i,k,s}(j)$. The cost for operating an aircraft of type k at age i in period j under scenario s is determined by parameter $C^f_{i,k}$ and the fuel price $\xi_s(j)$ in that period. To capture the dynamic nature of fuel prices, we introduce a changing trend parameter $\epsilon^f_s(j)$, which describes the magnitude of extended-phase fuel price changes at period j of scenario s. Equations (3.10) provide the formulas for calculating the fuel cost for age i aircraft of type k at period j in scenario s during extended phase, and equations (3.11) provide the formulas for computing the operating cost for age i aircraft of type k at period j in scenario s during extended phase.

$$F_{i,k,s}(j) = \bar{F}_{i,k}(j) \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, j \in \mathcal{J}_1, s \in \mathcal{S}, \tag{3.8}$$

$$F^2_{i,k}(j) = \bar{\xi}(j) C^f_{i,k} \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, j \in \mathcal{J}, \tag{3.9}$$

$$F^1_{i,k,s}(j) = (1 + \epsilon^f_s(j))\xi_s(j-1) C^f_{i,k} \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, j \in \mathcal{J}_2, s \in \mathcal{S}, \tag{3.10}$$

$$F_{i,k,s}(j) = F^1_{i,k,s}(j) + F^2_{i,k}(j) \quad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, j \in \mathcal{J}_2, s \in \mathcal{S}. \tag{3.11}$$

3.2 Demand

We use the set $\mathcal{U} = \{1, 2, 3, 4, 5, 6\}$ for demand types, where 1, 2, 3 represent short, medium, long flight distance passenger demand, and 4, 5, 6 represent short, medium, long flight distance cargo demand. We introduce parameters $D_{u,s}(j)$ to represent type u demand of scenario s in period j, where $u \in \mathcal{U}$, $s \in \mathcal{S}$ and $j \in \mathcal{J}$. We assume that the passenger-aircraft, freighter and the converted passenger-aircraft have three different flight range, which can satisfy different flight range demand.

In the decision phase, the demand is primarily derived from historical data of the airline as the deterministic parameter $\bar{D}_u(j)$. Airlines can meet their passenger and cargo demands during the decision phase through the acquisition of aircraft by either purchasing or leasing them.

In the extended phase, we introduce parameters $\epsilon^d_{u,s}(j)$ to describe the magnitude of changes in extended-phase demand of type u and scenario s at period j, considering the uncertainty in demand fluctuations. Equations (3.12)–(3.13) provide the calculation methods for decision phase demand and extended phase demand respectively.

$$D_{u,s}(j) = \bar{D}_u(j) \qquad \forall u \in \mathcal{U}, s \in \mathcal{S}, j \in \mathcal{J}_1, \tag{3.12}$$

$$D_{u,s}(j) = (1 + \epsilon^d_{u,s}(j))D_{u,s}(j-1) \qquad \forall u \in \mathcal{U}, s \in \mathcal{S}, j \in \mathcal{J}_2. \tag{3.13}$$

3.3 Discount Rate

In this study, we consider the time value of money by introducing the discount rate $\alpha_s(j)$, which represent the discount rate at the period j in the scenario s.

In the decision phase, the discount rate is primarily derived from historical data of the airline as deterministic parameter $\bar{\alpha}(j)$, similar to the demand in the decision phase. The airline manages the fleet composition by considering the time value of money.

In the extended phase, the parameter $\epsilon_s^r(j)$ is introduced to describe the magnitude of changes in extended-phase discount rate of scenario s at period j, which captures the uncertainty of the financial market. Equations (3.14)–(3.15) provide the calculation methods for discount rate in decision phase and extended phase respectively.

$$\alpha_s(j) = \bar{\alpha}(j) \qquad \forall s \in \mathcal{S}, j \in \mathcal{J}_1, \tag{3.14}$$

$$\alpha_s(j) = (1 + \epsilon_s^r(j))\alpha_s(j-1) \qquad \forall s \in \mathcal{S}, j \in \mathcal{J}_2. \tag{3.15}$$

Chapter 4

Model Formulation

4.1 Model Assumptions

In this section, we will illustrate the assumptions used in our optimization model. These assumptions cover the number of airlines being optimized, the operational capabilities of the airline, and the contractual agreements with leasing and selling companies.

1. Single Airline Optimization: Our model focuses on optimizing a single airline. The primary reason is that fleet management aims to inform strategic decisions. By modeling a single airline, we can concentrate on deriving managerial insights specific to that company, while its demand data already incorporate the effects of competition and cooperation with other airlines.

2. Aircraft Operational Reliability: We assume that each aircraft owned or leased by the airline is fully operational and capable of meeting its corresponding passenger and cargo demands without encountering any mechanical failures or unserviceable issues.

3. No Contractual Breaches or Delivery Delays: We assume there are no breach clauses in contracts between the airline, leasing companies, and aircraft selling companies. This means the airline will not incur penalty fees or cancel orders once an aircraft purchase or lease agreement is finalized. Additionally, we assume no delays in the delivery of leased aircraft.

4. Parameter Uncertainty in the Extended Phase: We assume that specific values for passenger demand, cargo demand, fuel prices, and discount rates are known with certainty during the decision phase. In the extended phase, however, these parameters become uncertain, while the probability distributions governing their year-to-year changes are assumed to be known. Uncertainty is modeled by generating scenarios from normal distributions with predetermined means and variances.

5. Simple Transformation of P2F: In our model, we only consider the simple P2F conversion, which involves removing passenger cabin items and replacing them with additional cargo space. This approach aligns with the current mainstream P2F method. Our P2F model does not account for updates or iterations to the aircraft engines.

4.2 Notations

In this section, we introduce the notations used in our optimization model in Table 4.1 for better readability.

Table 4.1: A Summary of Notations.

Sets

$\mathcal{J}_1$	Set of the periods in the decision phase;
$\mathcal{J}_2$	Set of the periods in the extended phase;
$\mathcal{K}_1$	Set of the types of passenger-aircraft;
$\mathcal{K}_2$	Set of the types of freighters;
$\mathcal{K}_3$	Set of the types of freighters converted from the passenger-aircraft;
$\mathcal{I}_k$	Set of the ages of type-k aircraft, where $k \in \mathcal{K}$;
$\mathcal{N}^o_{i,k}$	Set of operating-leasing periods of type-k aircraft of age i, where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$ and $i \in \mathcal{I}_k$;
$\mathcal{N}^c_{i,k}$	Set of capital-leasing periods of type-k aircraft of age i, where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$ and $i \in \mathcal{I}_k$;
$\mathcal{O}$	Set of payment periods during the process of repaying the purchase;
$\mathcal{U}$	Set of demand types;
$\mathcal{S}$	Set of scenarios of extended phase;

Parameters

$\alpha_s(j)$	Discount rate used to determine the present value of future cash flows at period j in the scenario s, where $j \in \mathcal{J}$ and $s \in \mathcal{S}$
$\beta(j)$	Maximum allowable unpaid debt of the airline in period j;
δ_u	Unit profit from fulfilling demand type u, where $u \in \mathcal{U}$;
$\rho_{i,k}(j)$	The number of all available type-k aircraft of age i at time j related to the decisions made before decision phase, where $k \in \mathcal{K}$, $i \in \mathcal{I}_k$ and $j \in \mathcal{J}$;
$\sigma_{i,k}(j)$	The number of all owned type-k aircraft of age i at time j related to the decisions made before decision phase, where $k \in \mathcal{K}$, $i \in \mathcal{I}_k$ and $j \in \mathcal{J}$;
$P_{i,k}(o)$	Principal and interest payments required at the payment period o during purchasing the type-k aircraft of age i, where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$ and $i \in \mathcal{I}_k$;
γ	The earliest period when the airline is able to acquire aircraft through purchases;
ω_s	Probability for scenario s;

$B^1_{i,k}$	Unit annual operating-leasing price for type-k aircraft of age i, where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$ and $i \in \mathcal{I}_k$;
$B^2_{i,k}$	Unit annual capital-leasing price for type-k aircraft of age i, where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$ and $i \in \mathcal{I}_k$;
$A_{i,k}$	Total expense required to convert a type-k passenger-aircraft of age i to a freighter, where $k \in \mathcal{K}_1$ and $i \in \mathcal{I}_k$;
$A_{i,k}(o)$	Principal and interest payments required at the period o during converting a type-k passenger-aircraft of age i to a freighter , where $k \in \mathcal{K}_1$ and $i \in \mathcal{I}_k$;
E^k_i	Maintenance cost for keeping type-k aircraft of age i, where $k \in \mathcal{K}$ and $i \in \mathcal{I}_k$;
$F_{i,k,s}(j)$	Operating cost of type-k aircraft in period j of scenario s, where $k \in \mathcal{K}$, $j \in \mathcal{J}$ and $s \in \mathcal{S}$;
$L_{i,k}$	Unit monetary value for owned type-k aircraft of age i , where $k \in \mathcal{K}$ and $i \in \mathcal{I}_k$;
C^u_k	Capacity of type-k aircraft for severing type u demand, where $k \in \mathcal{K}$ and $u \in \mathcal{U}$;
$D_{u,s}(j)$	Type-u demand of scenario s in period j, where $u \in \mathcal{U}$, $s \in \mathcal{S}$ and $j \in \mathcal{J}$;
$\underline{D}_{u,s}(j)$	Minimum type-u demand of scenario s that needs to be met in period j, where $u \in \mathcal{U}$, $s \in \mathcal{S}$ and $j \in \mathcal{J}_1$;
$H(j)$	Budget in period j, where $j \in \mathcal{J}_1$;
$M_{k,j}$	A sufficiently-large constant, where $k \in \mathcal{K}$ and $j \in \mathcal{J}$;
Variables	
$v_s(j)$	Net profit in period j of scenario s, where $j \in \mathcal{J}$ and $s \in S$;
$d_s(j)$	Operational cost in period j of scenario s, where $j \in \mathcal{J}$ and $s \in \mathcal{S}$;
$e_s(j)$	Revenue in period j of scenario s, where $j \in \mathcal{J}$ and $s \in \mathcal{S}$;
$g_{u,s}(j)$	The proportion of type u fulfilled by the airline in period j of scenario s, where $u \in \mathcal{U}$, $j \in \mathcal{J}$ and $s \in \mathcal{S}$;

$t(j)$	Unpaid debt from initial period to period j, $j \in \mathcal{J}$;
$\bar{q}_i^k(j)$	Number of all available type-k aircraft of age i in period j, where $k \in \mathcal{K}$, $i \in \mathcal{I}_k$, $j \in \mathcal{J}$;
$q_{i,u}^k(j)$	Number of available type-k aircraft of age i in period j satisfying type u demand, where $k \in \mathcal{K}$, $i \in \mathcal{I}_k$, $j \in \mathcal{J}$ and $u \in \mathcal{U}$;
$z_i^k(j)$	Number of all owned type-k aircraft of age i, where $k \in \mathcal{K}$, $i \in \mathcal{I}_k$, and $j \in \mathcal{J}$;
$p_i^k(j)$	Number of owned type-k aircraft of age i, sold in period j, where $k \in \mathcal{K}$, $i \in \mathcal{I}_k$, and $j \in \mathcal{J}_1$;
$x_i^k(j)$	Number of type-k aircraft of age i acquired through purchasing in period j, where $k \in \mathcal{K}$, $i \in \mathcal{I}_k$ and $j \in \mathcal{J}_1$;
$y_{i,n}^k(j)$	Number of type-k aircraft of age i for a lease period of n acquired through operating leases in period j , where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$, $i \in \mathcal{I}_k$, $j \in \mathcal{J}_1$ and $n \in \mathcal{N}_{i,k}^o$;
$s_{i,n}^k(j)$	Number of type-k aircraft of age i for a lease period of n acquired through capital leases in period j , where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$, $i \in \mathcal{I}_k$, $j \in \mathcal{J}_1$ and $n \in \mathcal{N}_{i,k}^c$;
$r_i^k(j)$	Number of type-k passenger-aircraft of age i converted into a freighter in period j, where $k \in \mathcal{K}_1 \cup \mathcal{K}_2$, $i \in \mathcal{I}_k$ and $j \in \mathcal{J}_1$.

4.3 Objective Function and Profit Calculation

$$\text{Maximize} \quad \textstyle\sum_{s\in\mathcal{S}} \omega_s \sum_{j\in\mathcal{J}} \frac{v_s(j)}{(1+\alpha_s(j))^j} \tag{4.1}$$

$$v_s(j) = e_s(j) - d_s(j) \quad \forall j \in \mathcal{J}, s \in \mathcal{S}. \tag{4.2}$$

The objective function (4.1) maximizes the airline's expected net profit through the planning horizon, where the parameter ω_s denotes the probability of scenario

s. By introducing the discount rate $\alpha_s(j)$, we consider the time value of money. Equations (4.2) provide the method for calculating the net profit of airline in each period of both decision phase and extended phase under each scenario.

In the following section, we present the constraints of our optimization model.

4.4 Constraints of Demand Fulfilling Rates

We introduce the proportion of demand of type u fulfilled by the airline in period j of scenario s as $g_{u,s}(j)$. This proportion represents the airline's ability to meet a certain percentage of demand by utilizing operational aircraft, both in decision phase or extended phase.

$$g_{u,s}(j) \leq \frac{\sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{I}_k} C_k^u q_{i,u}^k(j)}{D_{u,s}(j)} \qquad \forall j \in \mathcal{J}, u \in \mathcal{U}, s \in \mathcal{S} \tag{4.3}$$

$$g_{u,s}(j) \leq 1 \qquad \forall j \in \mathcal{J}, u \in \mathcal{U}, s \in \mathcal{S}, \tag{4.4}$$

$$g_{u,s}(j) \geq 0 \qquad \forall j \in \mathcal{J}, u \in \mathcal{U}, s \in \mathcal{S}. \tag{4.5}$$

Constraints (4.3) provide the calculation method for the decision variables $g_{u,s}(j)$. They respectively represent the proportion of demand fulfilled by the airline in period j to the total demand. Constraints (4.4) and constraints (4.5) provide the range of values for the decision variables $g_{u,s}(j)$.

4.5 Constraints of Revenues and Costs

$$e_s(j) = \sum_{u\in\mathcal{U}} \delta_u g_{u,s}(j) D_{u,s}(j) + \sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{I}k} Li,kp_i^k(j) + \sum_{k\in\mathcal{K}} L_{\overline{I}k,k} z\overline{I}_k{}^k(j)$$
$$\forall j \in \mathcal{J}, s \in \mathcal{S}. \tag{4.6}$$

$$\begin{aligned} d_s(j) = \sum_{k\in\mathcal{K}_1\cup\mathcal{K}_2} \Big(& \underbrace{\sum_{i=0}^{\overline{I}_k-\theta} \sum_{o=0}^{\min\{\theta-1,j\}} P_{i,k}(o) x_i^k(j-o)}_{Purchasing\ cost} + \underbrace{\sum_{i=0}^{\overline{I}_k-\theta} \sum_{o=0}^{\min\{\theta-1,j\}} A_{i,k}(o) r_i^k(j-o)}_{Converting\ cost} \\ & + \underbrace{\sum_{n=\max\{j-j_1+1,\underline{N}^o_{i,k}\}}^{\overline{N}^o_{i,k}} \sum_{j_1=0}^{j} \sum_{i\in\mathcal{I}_k} B^1_{i,k} y^k_{i,n}(j_1) + \sum_{n=\max\{j-j_1+1,\underline{N}^c_{i,k}\}}^{\overline{N}^c_{i,k}} \sum_{j_1=0}^{j} \sum_{i\in\mathcal{I}_k} B^2_{i,k} s^k_{i,n}(j_1)}_{Leasing\ cost} \\ & + \underbrace{\sum_{k\in\mathcal{K}_1\cup\mathcal{K}_2} \sum_{i\in\mathcal{I}_k} F^j_{i,k,s} \bar{q}^k_i(j)}_{Operating\ cost} + \underbrace{\sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{I}_k} E^k_i \bar{q}^k_i(j)}_{Maintenance\ cost} \qquad \forall j \in \mathcal{J}, s \in \mathcal{S}, \end{aligned} \tag{4.7}$$

$$d_s(j) \le H(j) \quad \forall j \in \mathcal{J}, s \in \mathcal{S}. \tag{4.8}$$

$$
\begin{aligned}
t(j) = \sum_{k \in \mathcal{K}_1 \cup \mathcal{K}_2} \Big(& \underbrace{\sum_{o=j-j_1+1}^{\theta-1} \sum_{j_1=\max\{0,j-\theta+2\}}^{j} \sum_{i=0}^{\overline{I}_k-\theta} P_{i,k}(o) x_i^k(j_1)}_{Purchasing\ cost} \\
& + \underbrace{\sum_{n=\max\{j-j_1+1,\underline{N}^c_{i,k}\}}^{\overline{N}^c_{i,k}} \sum_{j_1=0}^{j} \sum_{i \in \mathcal{I}_k} (n-j+j_1-1) B^2_{i,k} s^k_{i,n}(j_1)}_{Capital-leasing\ cost} \\
& + \underbrace{\sum_{n=\max\{j-j_1+1,\underline{N}^o_{i,k}\}}^{\overline{N}^o_{i,k}} \sum_{j_1=0}^{j} \sum_{i \in \mathcal{I}_k} (n-j+j_1-1) B^1_{i,k} y^k_{i,n}(j_1)}_{Operating-leasing\ cost} \\
& + \underbrace{\sum_{o=j-j_1+1}^{\theta-1} \sum_{j_1=\max\{0,j-\theta+2\}}^{j} \sum_{i=0}^{\overline{I}_k-\theta} A_{i,k}(o) r_i^k(j_1) \Big)}_{Converting\ cost} \quad \forall j \in \mathcal{J},
\end{aligned} \tag{4.9}
$$

$$
t(j) \le \beta(j) \quad \forall j \in \mathcal{J}. \tag{4.10}
$$

Constraints (4.6) represent the revenue of the airline in period j during decision phase and extended phase. The first term of constraints (4.6) represents the revenue obtained by the airline from meeting demands. The second term represents the revenue obtained by the airline from selling aircraft. The third term represents the profit obtained by the airline from decommissioning aircraft at the maximum age of use.

Constraints (4.7) represent the operating cost of the airline during decision phase and extended phase. First term of constraints (4.7) represents the aircraft purchasing costs in each period. On condition that repayment period for the aircraft purchase is larger than period j, for example airline has a 10-year repayment period for the aircraft purchase, we provide the following example. At the 5th period, the airline only needs to calculate the aircraft it bought from period $5 - min\{10 - 1, 5\}$ to period 5, which equals 0 to 5. On condition that repayment period for the aircraft purchase is smaller than period j, for example airline has a 5-year repayment period for the aircraft purchase, at the 12th period, the airline only needs to calculate the aircraft it bought from period $12 - min\{5 - 1, 12\}$ to period 12, which equals 8 to 12. Second term represents the cost of P2F. Third term represents the operating cost of type-k aircraft in period j, including the fuel cost and environmental cost. Fourth term represents the cost of aircraft leasing, which includes aircraft under both operating lease and capital lease. On condition that the minimum operating-leasing period $\underline{N}^o_{i,k}$, capital-leasing period $\underline{N}^c_{i,k}$ is 3 years, whereas the maximum operating-leasing period $\overline{N}^o_{i,k}$ capital-leasing period $\overline{N}^c_{i,k}$ is 20 years, we provide the following example. At the 5th period, since the airline might have leased aircraft in previous years, it only needs to consider the aircraft which it leased from period 0 to period 5. For the aircraft it leased in period 0, the airline needs to consider the leasing period from $max\{5 - 0 + 1, 3\}$ to 20 , which equals 6 to 20. For the aircraft it leased in period 4, the airline needs to consider the leasing period from $max\{5 - 4 + 1, 3\}$ to 20, which equals 3 to 20. Fifth term represents the maintenance cost.

Constraints (4.8) ensure that the airline's operating cost in each period does not exceed the budget.

Constraints (4.9) represent the unpaid debt of the airline. First term of constraints (4.9) represents the unpaid purchase expenses for aircraft. On condition that the repayment period for the aircraft is 10, we provide the following example. The airline in period 5 should pay the unpaid expense form the aircraft purchased from period max$\{0, 5 - 10 + 2\}$ to 5, which equals 0 to 5. Take the aircraft purchased in period 0 as an example, since the airline has paid the debt from period 0 to 5 of the purchasing cycle, the unpaid debt is from period max$\{0, 5-0+1\}$ to 9. The second term of constraints (4.9) represents the unpaid expenses for aircraft under capital lease. The third term of constraints (4.9) represents the unpaid expenses for aircraft under operating lease. On condition that the minimum operating-leasing period $\underline{N}^{o}_{i,k}$ is 3, we provide the following example. The airline in period 5 should pay the unpaid expense for the aircraft acquired through operating leases from period 0 to 5. If the airline acquired one aircraft through an operating lease in period 0 for 10 years. The airline's unpaid operating lease debt for aircraft is $10-5+0-1$ periods, which equals 4. The fourth term of constraints (4.9) represents the unpaid expenses for converting passenger-aircraft.

Constraints (4.10) ensure that the airline's unpaid debt in each period does not exceed the maximum limit of outstanding debt.

4.6 Constraints of Fleet Sizing

$$\bar{q}^{k}_{i}(j) = \sum_{u \in \mathcal{U}} q^{k}_{i,u}(j) \qquad \forall k \in \mathcal{K}, i \in \mathcal{I}_k, j \in \mathcal{J} \tag{4.11}$$

$$\bar{q}_i^k(j) = \underbrace{\rho_{i,k}(j) + \sum_{i_1 \in \{i-1\}\cap\mathcal{I}_k} \sum_{j_1 \in \{j-1\}\cap\mathcal{J}} \bar{q}_{i_1}^k(j_1)}_{\text{Aircraft acquired and remaining from previous period}} + \underbrace{x_i^k(j) + \sum_{n \in \mathcal{N}_{i,k}^o} y_{i,n}^k(j) + \sum_{n \in \mathcal{N}_{i,k}^c} s_{i,n}^k(j)}_{\text{Aircraft obtained by the airline in period } j}$$

$$- \underbrace{\sum_{n=\underline{N}_{i,k}}^{\min\{i,j,\overline{N}_{i,k}\}} \sum_{i_2 \in \{i-n\}\cap\mathcal{I}_k} \sum_{j_2 \in \{j-n\}\cap\mathcal{J}} y_{i_2,n}^k(j_2) - p_i^k(j) - r_i^k(j)}_{\text{Aircraft lost by the airline in period } j}$$

$$\forall j \in \mathcal{J},\ k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2,\ i \in \mathcal{I}_k. \tag{4.12}$$

$$\bar{q}_i^k(j) = \underbrace{\rho_{i,k}(j) + \sum_{i_2 \in \{i-1\}\cap\mathcal{I}_k} \sum_{j_2 \in \{j-1\}\cap\mathcal{J}} \bar{q}_{i_2}^k(j_2)}_{\text{Fleet size of the airline in period } j-1}$$

$$+ \underbrace{\sum_{k' \in K_1 : f(k')=k} \sum_{i_1 \in \{i-\iota_k\}\cap\mathcal{I}_k} \sum_{j_1 \in \{j-\iota_k\}\cap\mathcal{J}} r_{i_1}^{k'}(j_1)}_{\text{Freighters converted by the airline in period } j}$$

$$- \underbrace{p_i^k(j)}_{\text{Aircraft sold by the airline in period } j} \qquad \forall k \in \mathcal{K}_3,\ i \in \mathcal{I}_k,\ j \in \mathcal{J}. \tag{4.13}$$

Constraints (4.11)–(4.13) ensure that the number of aircraft in the airline's inventory reaches a balanced quantity in each period. Constraints (4.12) provide the sources of gaining and losing of passenger-aircraft for airlines at time periods excluding initial period. First term of constraints (4.12) represents the number of the aircraft which the airline acquired before the decision phase and the aircraft left at the former period. Second term of constraints (4.12) represents the aircraft acquired via three methods: purchasing, operating lease, and capital lease, and third term of constraints (4.12) represents the aircraft lost by the airline: aircraft with expiring operating lease agreements, sold aircraft and passenger-aircraft converted to freighters. On condition that the minimum operating lease period $\underline{N}^o_{i,k}$ is 3 years and the maximum operating-leasing period $\overline{N}^o_{i,k}$ is 20 years, the airline wants to calculate the number of aircraft with an age of 11 of type i in the 5th period . The number of such aircraft is initially composed of the aircraft of type i with an age of 10 in the 4th period. Then it is composed of the aircraft that the airline purchased, and acquired through operating leases and capital leases. The airline should return the aircraft it leased under operating lease from period $5 - \min\{11, 5, 20\}$ to period $5 - 3$, which corresponds to the 0th period to the 2nd period. The number of aircraft of type i should also be reduced by the number of aircraft sold and the number of aircraft converted.

Constraints (4.13) ensure that the number of freighters converted by passenger-aircraft in the airline's inventory reaches a balanced quantity in each period. We introduce parameter ι_k as time period represents the duration required for converting type-k passenger-aircraft into freighters. First term of constraints (4.13) represents the number of freighters from the period beyond decision phase. Second term represents the number of the freighters converted from passenger-aircraft. Third term represents the number of the freighters sold by the airline.

$$
\begin{aligned}
z_i^k(j) = \quad & \underbrace{\sigma_{i,k}(j) + \sum_{i_1 \in \{i-1\} \cap \mathcal{I}_k} \sum_{j_1 \in \{j-1\} \cap \mathcal{J}} z_{i_1}^k(j_1)}_{Aircraft\ acquired\ and\ remaining\ from\ previous\ period} \\
+ \quad & \underbrace{\sum_{i_2 \in \{i-\theta\} \cap \mathcal{I}_k} \sum_{j_2 \in \{j-\theta\} \cap \mathcal{J}} x_{i_2}^k(j_2)}_{Aircraft\ acquired\ through\ purchasing\ in\ period\ j} \\
+ \quad & \underbrace{\sum_{n \in \mathcal{N}_{i,k}^c} \sum_{i_3 \in \{i-n\} \cap \mathcal{I}_k} \sum_{j_3 \in \{j-n\} \cap \mathcal{J}} s_{i_3,n}^k(j_3)}_{Aircraft\ acquired\ through\ capital-leases\ in\ period\ j} \quad - \quad \underbrace{p_i^k(j) - r_i^k(j)}_{Aircraft\ lost\ in\ period\ j} \\
& \forall i \in \mathcal{I}_k, k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, j \in \mathcal{J},
\end{aligned}
\tag{4.14}
$$

$$
z_i^k(j) = \bar{q}_i^k(j) \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}_3, i \in \mathcal{I}_k, \tag{4.15}
$$

$$
\sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}_k} C_k^u q_{i,u}^k(j) \geq \underline{D}_{u,s}(j) \qquad \forall j \in \mathcal{J}_1, u \in \mathcal{U}, s \in \mathcal{S}. \tag{4.16}
$$

Constraints (4.14) ensure that the number of owned aircraft of the airline reaches a balanced quantity in each period and the airline can only sell the aircraft after the principal and interest for both purchasing and capital-leasing the aircraft have been fully repaid. Constraints (4.14) also ensure that the airline can only sell or convert passenger-aircraft that are already owned. First term of constraints (4.14) represents the number of the aircraft which the airline acquired before the decision phase and the aircraft left at the former period. Second term represents the aircraft obtained by the airline through purchases. Third term represents the aircraft obtained by the airline through capital leases. Fourth term represents the number of the aircraft which the airline sells or converted to freighters. Constraints (4.15) specify that a freighter converted from the passenger-aircraft can only be obtained by converting the passenger-aircraft already owned by the airline. Constraints (4.16) ensure that the airline meets the minimum requirement for demand at time j within decision phase with the available aircraft.

4.7 Constraints of Operation of Aircraft

$$x_i^k(j) = 0 \quad \forall k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, i \in \mathcal{I}_k, j \in \mathcal{J} : j < \gamma \vee j > \overline{J}_1, \tag{4.17}$$

$$x_i^k(j) = 0 \quad \forall k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, i \in \mathcal{I}_k : i \geq \overline{I}_k - \theta, j \in \mathcal{J}, \tag{4.18}$$

$$y_{i,n}^k(j) = 0 \quad \forall j \in \mathcal{J}_2, k \in \mathcal{K}, i \in \mathcal{I}_k : k \in \mathcal{K}_1 \cup \mathcal{K}_2, n \in \mathcal{N}_{i,k}^o, \tag{4.19}$$

$$s_{i,n}^k(j) = 0 \quad \forall j \in \mathcal{J}_2, k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, i \in \mathcal{I}_k, n \in \mathcal{N}_{i,k}^c, \tag{4.20}$$

$$r_i^k(j) = 0 \quad \forall j \in \mathcal{J}, k \in \mathcal{K} : k \in \mathcal{K}_2, i \in \mathcal{I}_k, \tag{4.21}$$

$$r_i^k(j) = 0 \quad \forall j \in \mathcal{J}, k \in \mathcal{K} : k \in \mathcal{K}_1, i \in \mathcal{I}_k : i \geq \overline{I}_k - \iota_k, \tag{4.22}$$

$$r_i^k(j) = 0 \quad \forall j \in \mathcal{J}_2, k \in \mathcal{K} : k \in \mathcal{K}_1, i \in \mathcal{I}_k, \tag{4.23}$$

$$p_i^k(j) = 0 \quad \forall j \in \mathcal{J}_2, k \in \mathcal{K} : k \in \mathcal{K}, i \in \mathcal{I}_k. \tag{4.24}$$

Constraints (4.17) and constraints (4.18) ensure that the airline can not acquire aircraft through purchasing during periods when they are not available for acquisition, as well as outside the decision phase. Additionally, these constraints guarantee that the purchased aircraft have residual useful life remaining after becoming assets. Constraints (4.19) and constraints (4.20) ensure that the airline can only acquire aircraft through operating leases and capital leases in the decision phase. Constraints (4.21)–(4.23) ensure that the airline can only convert passenger-aircraft into freighters, while also ensuring that there is still remaining useful life after the conversion. Additionally, these constraints prohibit the airline from converting passenger-aircraft into freighter outside the decision phase. Constraints (4.24) ensure that the airline can only sell the aircraft in the decision phase.

4.8 Domains of Decision Variables

$$x_i^k(j) \in \mathbb{N} \qquad \forall k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, i \in \mathcal{I}_k, j \in \mathcal{J}, \tag{4.25}$$

$$y_{i,n}^k(j) \in \mathbb{N} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}, i \in \mathcal{I}_k : k \in \mathcal{K}_1 \cup \mathcal{K}_2, n \in \mathcal{N}_{i,k}^o, \tag{4.26}$$

$$s_{i,n}^k(j) \in \mathbb{N} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, i \in \mathcal{I}_k, n \in \mathcal{N}_{i,k}^c, \tag{4.27}$$

$$r_i^k(j) \in \mathbb{N} \qquad \forall k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, i \in \mathcal{I}_k, j \in \mathcal{J}, \tag{4.28}$$

$$p_i^k(j) \in \mathbb{N} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K} : k \in \mathcal{K}_1 \cup \mathcal{K}_2, i \in \mathcal{I}_k, \tag{4.29}$$

$$\bar{q}_i^k(j) \in \mathbb{N} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}, i \in \mathcal{I}_k, \tag{4.30}$$

$$q_{i,u}^k(j) \in \mathbb{N} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}, i \in \mathcal{I}_k, \tag{4.31}$$

$$z_i^k(j) \in \mathbb{N} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}, i \in \mathcal{I}_k, \tag{4.32}$$

$$v_s(j) \in \mathbb{R} \qquad \forall j \in \mathcal{J}, s \in \mathcal{S}, \tag{4.33}$$

$$d_s(j) \in \mathbb{R} \qquad \forall j \in \mathcal{J}, s \in \mathcal{S}, \tag{4.34}$$

$$e_s(j) \in \mathbb{R} \qquad \forall j \in \mathcal{J}, s \in \mathcal{S}, \tag{4.35}$$

$$t(j) \in \mathbb{R} \qquad \forall j \in \mathcal{J}, \tag{4.36}$$

$$f^k(j) \in \{0, 1\} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}. \tag{4.37}$$

Finally, constraints (4.25)–(4.37) impose integer and binary status on the model's decision variables.

Chapter 5

Methodology

5.1 Analysis of Complexity

In this section, we prove that the fleet management problem introduced in Section 3 is NP-hard. For ease of analysis, we consider a simplified version of the problem with only one period, one scenario, and customer demand as the sole constraint. In addition, we assume that the airline can only use operating leases and that the sole cost associated with operating aircraft is maintenance. Even under these restrictive assumptions, we demonstrate that the problem remains computationally challenging by reducing a known NP-hard problem to it. Specifically, given parameters $D_1(j)$, $B^1_{i,k}$, E^k_i, and $H(j)$, it cannot be determined in polynomial time whether the profit of the problem, denoted by R, is at least a given constant R_c, unless $NP = P$. We prove this by a reduction from the Unbounded Knapsack Problem.

Theorem 1. The fleet management problem is NP-hard.

Proof. We transform the Unbounded Knapsack Problem to the decision version of the fleet management problem. The Unbounded Knapsack Problem can be stated as follows. Given a set of K items and a knapsack, with profit p_k of item k, weight w_k of item k, capacity c of the knapsack. We define N_k as the number of type-k items placed in the knapsack. Each type of item is available in unlimited quantities. We need to maximize the profit P from loading items while ensuring that the capacity constraints of the knapsack are not exceeded and make guarantee that the profit P is no less than P_c. This problem has been proven to be NP-hard, as noted in Kellerer et al. (2004).

Given an arbitrary instance of the Unbounded Knapsack Problem, we construct a corresponding instance of the fleet management problem. In the simplified fleet management problem, the airline needs to ensure that the cost of leasing and maintaining aircraft does not exceed $H(0)$. Therefore, we assume that the maximum passenger demand that can be accommodated is $\frac{P_c}{\delta_1}$, which will not exceed the airline's maximum financial limit. We assume constants C which is greater than 0 and use the formula constraints (5.1) to ensure that customer demand can be met at the maximum level of service capacity that the airline can provide during this time period. Additionally, we assume that the passenger demand for the airline in the decision phase is infinite. In this section, we have modified the decision variables $y_{i,n}^k(j)$ to take the form of l_k to represent the number of type-k aircraft leased by the airline in the first stage. Specifically, we set parameters in the problem as follows:

$$
\begin{aligned}
D_1(0) &= \tfrac{P_c}{\delta_1} + C, && (5.1)\\
B^1_{0,k} + E^k_0 &= w_k \quad \forall k \in K, && (5.2)\\
H(0) &= c, && (5.3)\\
\delta_1 C^1_k &= p_k \quad \forall k \in K, && (5.4)\\
R_c &= P_c. && (5.5)
\end{aligned}
$$

Clearly, this transformation can be completed in polynomial time. We will show that there exists a feasible solution to the constructed instance of our problem if and only if the answer to the Knapsack Problem is “yes”.

Suppose the answer to the Knapsack Problem is “yes”. Let N^*_k denote the items selected to be packed in the knapsack, and l^*_k denote the number of aircraft under operating lease by airline in the first time period. Clearly, we have $\sum_{k\in K} w_k N^*_k \leq c$. Then according to Constraints (5.1)–(5.3), we can determine that the airline’s expenses in the first time period will not exceed the maximum financial requirement. Then, according to $Z = \sum_{k\in K} \delta_1 C^1_k l_k$ and the constraints (5.4), we can find out that the $Z^* = \sum_{k\in K} \delta_1 C^1_k l^*_k = \sum_{k\in K} p_k N^*_k \geq P_c = R_c$. Then, l^*_k is feasible to the constructed instance of the fleet management problem.

Conversely, suppose that the answer to the fleet management problem is “yes” and there exists a l^*_k not only can it meet the financial requirements of the first time period, but it also satisfies that it is greater than the constant R_c. We set N^*_k as the quantity type-k items placed into the knapsack. According to constraints (5.1)–(5.3), we can find out that $\sum_{k\in K}(B^1_{0,k} + E^k_0) l^*_k = \sum_{k\in K} w_k N^*_k \leq c$, which means that the item put into the knapsack will not exceed the payload. Then according to constraints (5.4), we can say that $P^* = \sum_{k \in K} p_k N_k^* = \sum_{k \in K} \delta_1 C_k^1 l_k^* \geq R_c = P_c$. Then, N_k^* is feasible to the unbounded knapsack problem. $\square$

Remark:

In the proof of Theorem 1, the constructed instance of the fleet management problem involves only one time period, one scenario, and restricts the airline to operating leases only, without allowing for aircraft purchases or P2F conversions. Therefore, the fleet management problem addressed in our research is also NP-hard.

5.2 Rolling-horizon Approach

In this section, we will introduce the solving methodology which can be applied in our model, Rolling-horizon Approach (RHA).

The rolling horizon method is employed to determine the decision variables for both the decision phase and the extended phase over a multi-period planning horizon. This approach addresses the dynamic and uncertain nature of real-world airline operations. Considering that airlines continuously update their decisions based on new information, our rolling horizon approach provides a practical framework for sequential decision-making.

This approach, detailed in Algorithm 1, iteratively solves the optimization problem over a moving window of periods. In each iteration, the model makes decisions for the current decision phase and accounts for future uncertainties in an extended phase. Only the decisions for the first period of the decision phase are implemented, and the process then rolls forward, updating initial conditions and parameters based on the realized outcomes for the next iteration. The illustration of the approach can be found in Figure 5.1.

Algorithm 1 Rolling-horizon Approach

Require:

Decision phase periods: T_1

Extended phase periods: T_2

Scenario type set: $\mathcal{S}$

Decision variable set: $\mathcal{V}$

Initial fleet state: $\rho_0 = \{\rho_{i,k}^0\}$

Total planning periods: T_{total}

Initialize: $\rho(0) \leftarrow \rho_0$, solution set $\mathcal{V}^* \leftarrow \emptyset$

Solve optimization for window $t \in [1, T_1 + T_2]$ with $\rho(0)$

Extract first-period decision: $v_1^* \in \mathcal{V}$

Update: $\mathcal{V}^* \leftarrow \mathcal{V}^* \cup \{v_1^*\}$

for $t = 1$ **to** T_{total} **do**

  Set decision phase: $\mathcal{J}_1 = [t, t + T_1 - 1]$

  Set extended phase: $\mathcal{J}_2 = [t + T_1, t + T_1 + T_2 - 1]$

  Update fleet state: $\rho(t) \leftarrow v_t^*$

  Solve stochastic program for window $t \in [t, t + T_1 + T_2 - 1]$

  Extract first-period decision: $v_t^* \in \mathcal{V}$

  Update: $\mathcal{V}^* \leftarrow \mathcal{V}^* \cup \{v_t^*\}$

end for

  return $\mathcal{V}^* = \{v_t^*\}_{t=1}^{T_{\text{total}}}$

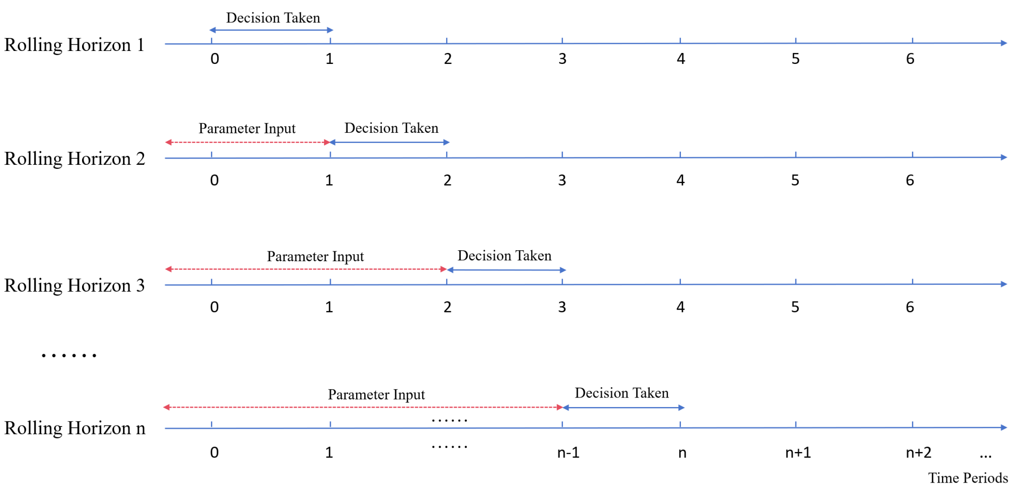

Figure 5.1: Illustration of Rolling-horizon Approach.

We acknowledge the critical importance of the RHA for real-world dynamic decision-making, particularly in volatile environments like the airline industry. Indeed, we propose and recommend the use of the RHA for airlines to effectively manage their fleet over time, adapting to continuously evolving market conditions and operational uncertainties.

However, the results of the numerical experiments and sensitivity analysis presented in our research are derived from a single, comprehensive optimization run of our model, rather than from an iterative RHA simulation. This approach is justified because our model's design inherently incorporates an extended phase that explicitly accounts for future uncertainty. This means that our single optimization is not a static snapshot; instead, it is a forward-looking decision that has been optimized against a spectrum of anticipated future scenarios or uncertainty bounds.

Chapter 6

Numerical Experiments

In this section, we conduct two sets of experiments. The first set of experiments evaluates the effectiveness of the model, while the second set focuses on performing sensitivity analysis on different parameters. All our numerical experiments are based on Python code and are solved using Gurobi version 10.0.2. The computer used has an Intel(R) Core(TM) i7-13700HX processor running at 2.10 GHz with 16.0 GB of RAM. We set 3,600 seconds as the time limit for the solver when solving any instance in the experiments. Section 6.1 introduces the experimental design, Section 6.2 presents the results of the numerical experiments, and Section 6.3 discusses the results of the sensitivity analysis.

6.1 Experiment Design

For the set of numerical experiments, we consider a total of eight periods during the decision phase, as well as 20 periods in the extended phase, with each period corresponding to one year in a real-world scenario. We set the discount rate $\alpha_s(j)$ in the decision phase to 0.5%, representing a low-risk financial market environment. The oil price is set at 2.85 USD per gallon from Sourasis Bose (2023) and the environmental cost is set at 0.39 USD per gallon from University of California, Irvine (2016) for the first set of numerical experiments and the baseline of the sensitivity analysis. We consider three types of airlines: small, medium, and large. Specifically, data from Loganair is used to represent the small airline category, serving as a representative European regional carrier. For the medium airline category, we employ data from Cathay Pacific, which is representative of an Asian airline operating both significant passenger and cargo demands. Finally, Delta Air Lines being the world's second-largest airline by domestic passenger kilometers and passenger fleet size, is chosen to represent the large airline category.

Table 6.1 shows the aircraft parameter data used in the numerical experiment and sensitivity analysis. The columns are defined as follows: PL represents the payload capacity of an aircraft, for passenger-aircraft, it indicates the maximum number of passengers they can carry, while for cargo plane, it represents the payload capacity in tons. PE represents the price of purchasing a new aircraft, LE represents the price of aircraft under operating lease, LEN represents the price of whole new aircraft under operating lease, LEO represents the price of old aircraft under operating lease. WC represents whether the aircraft type supports conversion into a freighter (Y stands for yes and N for no), CE represents the cost of converting the aircraft, and CL represents the cargo capacity of the aircraft after conversion. PE, LEN, LEO and CE are measured in million US dollars. The typical seat capacity for passenger aircraft and payload capacity for freighters are sourced from Airbus (airbus.com), Boeing (boeing.com), Embraer (embraercommercialaviation.com), ATR (atr-aircraft.com), and Saab (saab.com).

Aircraft leasing prices and current values for new aircraft are derived from reports from companies including IBA (iba.aero), Cirium (cirium.com), ISTAT (istat.org), and AVAC (aircraftvalues.com). P2F conversion costs and post-transformation payload data are obtained from IBA (iba.aero) and Elbe Flugzeugwerke (elbe-flugzeugwerke.com). The fleet data for Loganair (airfleets.net), Cathay Pacific (Cathay Pacific, 2025), and Delta Air Lines (Delta Air Lines, 2025) in 2019 are shown in Table 6.2. It should be noted that both Loganair and Delta Air Lines are primarily passenger-focused carriers, with their cargo needs mainly met through the belly capacity of passenger aircraft. As a result, dedicated freighters are not included for these airlines in our numerical experiments.

For the computational performance analysis, we conduct ten numerical experiments for each type of airline. The difference among experiments for the same type of airline lies in the initial fleet size. Specifically, we use the fleet data of 2019 in Table 6.2 as the mean of a normal distribution with a variance of 1, and generate different initial fleet sizes for each experiment accordingly. We assume that both passenger and cargo demand remain unchanged from the first period to the last period, and there is no uncertainty in the first set of numerical experiments to represent the stable and unchanging environment. Additionally, we assume that airlines of different scales have sufficient budget for their operations in the first set of experiments, and airlines will not consider the constraints of unpaid debt. Through preliminary experiments, we find in the dataset that when the constraints for unpaid debt and budget reach 2,000,000 million USD, neither unpaid debt nor budget has any impact on the airline's decisions and revenues. Therefore, we set these two parameters as 2,000,000 million USD when the airline does not consider the impact of unpaid debt and budget.

Table 6.1: Parameters of the Aircraft Types Used in Numerical Experiment

Name	PL	PE (Million USD)	LE (Million USD)		WC	CE (Million USD)	CL (Tons)
			LEN	LEO			
Passenger-aircraft							
A320-200	150	32.7	3.7	0.7	Y	5	21
A330-300	251	55.3	6.2	1	Y	18	63
B777-300	368	85.6	10.8	2.3	Y	28	100
B777-300ER	368	85.6	10.8	2.3	Y	28	100
B737-800	189	36.8	2.5	1.3	Y	4.2	24
B767-300ER	261	60	7.4	3.7	Y	14.7	53
A321-200	220	44.8	2.9	1.5	Y	6.1	28
A340-300	295	55	6.2	1	N	-	-
A350-900	280	148.4	16.6	1.8	N	-	-
A350-1000	334	165.3	18.5	2	N	-	-
B737-900ER	200	40	3	1	N	-	-
B757-200	220	25	3	1.8	N	-	-
A319-100	140	25	3.5	2	N	-	-
Embraer ERJ-145	50	15	2.5	1.2	Y	3	6.4
ATR 42	46	12	2	1	N	-	-
Saab 340	34	8	1.5	0.8	N	-	-
Freighter							
B747-400ERF	112	135.6	14.3	0.6	-	-	-
B747-8F	139	173	19.6	1.5	-	-	-

Table 6.2: Fleet Data of Loganair, Cathay Pacific, and Delta Air Lines in 2012 and 2019

Aircraft Type	**Loganair**			**Cathay Pacific**			**Delta Air Lines**		
	2012	2019	Change	2012	2019	Change	2012	2019	Change
A320-200	0	0	0	0	0	0	72	62	-10
A330-300	0	0	0	38	43	+5	30	32	+2
B777-300ER	0	0	0	36	53	+17	0	0	0
B737-800	0	0	0	0	0	0	77	77	0
B767-300ER	0	0	0	0	0	0	60	56	-4
A321-200	0	0	0	0	0	0	0	96	+96
A340-300	0	0	0	15	0	-15	0	0	0
A350-900	0	0	0	0	26	+26	0	0	0
B737-900ER	0	0	0	0	0	0	10	130	+120
B757-200	0	0	0	0	0	0	100	100	0
A319-100	0	0	0	0	0	0	57	148	+91
Embraer ERJ-145	3	13	+10	0	0	0	0	0	0
ATR 42	2	10	+8	0	0	0	0	0	0
Saab 340	15	12	-3	0	0	0	0	0	0
B747-400ERF	0	0	0	6	6	0	5	4	-1
Total	20	35	+15	95	128	+33	411	705	+294

6.2 Computational Performance and Advantages of Integrated Programming

6.2.1 Computational Performance

In this section, we conduct computational performance experiments to validate the effectiveness of our optimization model. We use type S to represent small airlines, type M for medium airlines, and type L for large airlines. Following the method described in Section 6.1, we generate 10 independent experiments for each airline type to test fleet management strategies under varying initial fleet sizes.

We use Table 6.3 to summarize the results of the first set of experiments, the columns are defined as follows: AT represents the scale of airline. GAP(%) represents the difference between the solution obtained from the optimization model and the solution to the relaxed problem. NPV represents the result of optimization, measured in million USD. NP represents the number of purchased aircraft. NPP represents the number of purchased passenger-aircraft, NPC represents the number of purchased freighter, NS represents the number of sold aircraft, ND represents the number of retired aircraft. NOL represents the number of aircraft under operating lease. PNOL represents the number of passenger-aircraft under operating lease. FNOL represents number of freighters under operating lease. NCL represents the aircraft under capital lease. PNCL represents the passenger-aircraft under capital lease. FNCL represents freighters under capital lease. NCF represents the number of converted passenger-aircraft. AVG represents the average of the numbers in the column of the table. The results of the experiments are summarized in Table 6.3 below:

Table 6.3: Results of Computational Performance.

Index	AT	Gap(%)	NPV	NP		NS	ND	NOL		NCL		NCF
				NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	S	0.0	694.55	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
2	S	0.0	702.97	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
3	S	0.0	661.84	0.0	0.0	32.0	0.0	57.0	0.0	0.0	0.0	0.0
4	S	0.0	684.24	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
5	S	0.0	694.55	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
6	S	0.0	728.50	0.0	0.0	37.0	0.0	57.0	0.0	0.0	0.0	0.0
7	S	0.0	727.27	0.0	0.0	38.0	0.0	57.0	0.0	0.0	0.0	0.0
8	S	0.0	694.55	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
9	S	0.0	711.66	0.0	0.0	37.0	0.0	57.0	0.0	0.0	0.0	0.0
10	S	0.0	694.55	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
-	AVG	0.0	699.47	0.0	0.0	35.4	0.0	57.0	0.0	0.0	0.0	0.0
11	M	0.1	194971.20	150.0	10.0	188.0	150.0	260.0	19.0	0.0	0.0	5.0
12	M	0.1	194467.28	150.0	10.0	181.0	150.0	266.0	20.0	0.0	0.0	6.0
13	M	0.1	195319.62	150.0	10.0	186.0	150.0	251.0	20.0	0.0	0.0	5.0
14	M	0.1	194679.72	150.0	10.0	184.0	150.0	256.0	20.0	0.0	0.0	6.0
15	M	0.1	195231.44	150.0	10.0	188.0	150.0	255.0	20.0	0.0	0.0	4.0
16	M	0.1	195229.11	150.0	10.0	193.0	150.0	255.0	19.0	0.0	0.0	5.0
17	M	0.1	195179.84	150.0	10.0	188.0	150.0	248.0	20.0	0.0	0.0	4.0
18	M	0.09	195244.77	150.0	10.0	187.0	150.0	249.0	20.0	0.0	0.0	4.0
19	M	0.1	194670.52	150.0	10.0	182.0	150.0	262.0	20.0	0.0	0.0	4.0
20	M	0.1	194164.19	150.0	10.0	178.0	150.0	268.0	20.0	0.0	0.0	4.0
-	AVG	0.1	194915.77	150.0	10.0	185.5	150.0	257.0	19.8	0.0	0.0	4.7
21	L	0.03	701915.12	1324.0	0.0	669.0	1324.0	2650.0	0.0	0.0	0.0	0.0
22	L	0.03	701879.84	1324.0	0.0	667.0	1324.0	2650.0	0.0	0.0	0.0	0.0
23	L	0.03	701877.03	1324.0	0.0	666.0	1324.0	2650.0	0.0	0.0	0.0	0.0
24	L	0.03	706218.70	1324.0	0.0	1037.0	1324.0	2650.0	0.0	0.0	0.0	0.0
25	L	0.03	701949.97	1324.0	0.0	670.0	1324.0	2650.0	0.0	0.0	0.0	0.0
26	L	0.03	701945.50	1324.0	0.0	671.0	1324.0	2650.0	0.0	0.0	0.0	0.0
27	L	0.03	701939.75	1324.0	0.0	671.0	1324.0	2650.0	0.0	0.0	0.0	0.0
28	L	0.03	701895.25	1324.0	0.0	669.0	1324.0	2650.0	0.0	0.0	0.0	0.0
29	L	0.03	701928.98	1324.0	0.0	667.0	1324.0	2650.0	0.0	0.0	0.0	0.0
30	L	0.03	701953.67	1324.0	0.0	671.0	1324.0	2650.0	0.0	0.0	0.0	0.0
-	AVG	0.03	702350.38	1324.0	0.0	705.8	1324.0	2650.0	0.0	0.0	0.0	0.0

From Table 6.3, we can see that within the allocated solution time, the model achieves a gap of less than 0.3%, which indicates that the model demonstrates high solution efficiency. Under stable demand, sufficient budget conditions, and the absence of a maximum allowable unpaid debt constraint, airlines of different sizes primarily meet their demand through purchasing aircraft and operating leases. As for the initial fleet of the airline, we can find that most of the aircraft are chosen to be sold within the decision phase, and the airline meets its passenger and cargo demand primarily through operating leases and purchasing. For medium airlines that simultaneously face high passenger and cargo demand, retaining a small portion of aircraft for P2F conversions is a beneficial strategy for profitability. In contrast, for small airlines focused primarily on passenger demand as well as for large airlines, selling older aircraft and introducing newer models represents a profitable approach.

6.2.2 Benefits of multiple aircraft acquisition strategies

In this section, we compare the performance of integrated programming with the single-perspective model. We consider the scenario in which the airline is not allowed to purchase aircraft, lease aircraft, or perform P2F conversions. We use Type IO to represent the integrated modeling methods, as illustrated in Section 4. We use Type NL to represent modeling methods where the airline is not allowed to lease aircraft. We use Type NB to represent modeling methods where the airline is not allowed to purchase aircraft and Type NC to represent the method where airline is not allowed to do P2F. Column OT represents different modeling methods. The results of the experiments are summarized in Table 6.4 below:

Table 6.4: Comparison of Different Modeling Methods.

Index	AT	OT	Gap(%)	NPV	NP		NS	ND	NOL		NCL		NCF
					NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	S	IO	0.0	694.55	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
2	S	NL	0.05	-1711.71	4.0	0.0	29.0	10.0	0.0	0.0	0.0	0.0	0.0
3	S	NB	0.0	694.55	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
4	S	NC	0.06	694.55	0.0	0.0	35.0	0.0	57.0	0.0	0.0	0.0	0.0
5	M	IO	0.1	194971.20	150.0	10.0	188.0	150.0	260.0	19.0	0.0	0.0	5.0
6	M	NL	0.1	175094.58	150.0	10.0	189.0	150.0	0.0	21.0	0.0	0.0	4.0
7	M	NB	0.1	186586.17	0.0	0.0	183.0	137.0	241.0	13.0	137.0	5.0	10.0
8	M	NC	0.1	189839.28	150.0	12.0	193.0	150.0	234.0	18.0	0.0	0.0	0.0
9	L	IO	0.03	701915.12	1324.0	0.0	669.0	1324.0	2650.0	0.0	0.0	0.0	0.0
10	L	NL	0.1	461532.10	1326.0	0.0	629.0	1326.0	0.0	0.0	0.0	0.0	40.0
11	L	NB	0.03	678612.33	0.0	0.0	669.0	572.0	3403.0	0.0	572.0	0.0	0.0
12	L	NC	0.04	701915.12	1324.0	0.0	669.0	1324.0	2650.0	0.0	0.0	0.0	0.0

Table 6.4 highlights the advantages of the integrated optimization approach used in our study. The results demonstrate the critical importance of leasing for small regional airlines: without leasing, it becomes nearly impossible to operate profitably. For medium-sized airlines, all purchasing aircraft, leasing aircraft, and P2F conversion aircraft play significant roles, and the integrated optimization approach consistently delivers the best performance. For large airlines, both the integrated optimization approach and the scenario without P2F restrictions yield the most favorable outcomes. Overall, based on the results in Table 6.4, we confirm the superiority of our integrated modeling approach across different categories of airlines, as compared with the single-perspective model.

6.3 Sensitivity Analysis

As for the sensitivity analysis, we assume the managerial insights derived from different types of airlines, consisting of the small airlines, medium airlines and the large airlines. The sensitivity analysis will include different parameters used in our optimization model, providing substantial insights for different areas, including the influence of maximum debt, maximum allowable unpaid debt and the influence of environmental policy. These parameters were selected due to their critical relevance: maximum debt directly impacts an airline's primary fleet management decisions, unpaid debt is crucial for understanding an airline's financial health and stability and the influence of environmental cost is fundamental to an airline's long-term sustainability initiatives.

We conduct the sensitivity analysis using the passenger and cargo data from 2012 to 2019 to exclude the impact of the COVID-19. Table 6.5 shows the decision-phase demand data of the airline in the sensitivity analysis. (UK Civil Aviation Authority, 2025; Cathay Pacific, 2025; Delta Air Lines, 2025). We use the fleet data of different airlines in 2012 as the parameters for the initial fleet size, shown in Table 6.2.

Table 6.5: Passenger and Cargo Demand of Loganair, Delta Air Lines, and Cathay Pacific from 2012 to 2019

Airline	Demand Type	2012	2013	2014	2015	2016	2017	2018	2019
Loganair	Passenger	544	558	573	588	603	619	635	650
	Cargo	6	6	6	6	6	7	7	7
Cathay Pacific	Passenger	28,961	29,920	31,570	34,065	34,233	34,820	35,468	35,233
	Cargo	1,563	1,539	1,723	1,798	1,854	2,056	2,152	2,022
Delta Air Lines	Passenger	160,000	165,600	171,396	177,395	183,604	190,030	196,681	204,000
	Cargo	900	926	953	981	1,009	1,038	1,068	1,100

Passenger demand is measured in thousands of passengers, and cargo demand is measured in thousands of tons.

6.3.1 Generation Methods of Different Scenarios

In this section, we present the methods used in our research to generate different scenarios for future development. We consider three distinct scenarios, labeled A, B, and C, each reflecting different trends in future demand fluctuations. Scenario A represents a surge in cargo demand driven by e-commerce growth or supply chain shifts. Scenario B captures an increase in passenger demand resulting from tourism booms, business travel recovery, or overall economic prosperity. Scenario C is designed as a stress test, simulating the impact of a prolonged global pandemic to evaluate model robustness. Table 6.6 summarizes the assumed trends in passenger demand, cargo demand, oil prices, and discount rates across three airlines (Loganair, Cathay Pacific, and Delta Air Lines) for these scenarios. For the extended phase (2020–2039), we assume that the annual change rate for parameter p of airline a in period k under scenario s follows a normal distribution, $\mathcal{N}(\mu_{s,a,p,k}, \sigma_{s,a,p,k})$. Each entry in Table 6.6 provides the corresponding mean

$\mu_{s,a,p,k}$ and standard deviation $\sigma_{s,a,p,k}$ for each parameter, airline, scenario, and time period. As described in Kim et al. (2014), we generate sub-scenarios for the extended phase by applying the Sample Average Approximation (SAA) method in combination with Monte Carlo simulation. For each scenario type, 10 distinct realizations are generated for sensitivity analysis. While our scenario generation methods are intended to provide plausible outlooks, it is important to acknowledge that the underlying parameters, especially those for long-term projections, are subject to significant uncertainty due to the unpredictability of the future, limitations in available data, and model simplifications. The mean and variance parameters for each scenario are derived from the World Bank Open Data, as referenced in World Bank (2025).

Table 6.6: Estimated Yearly Change Rates for Scenarios A–C (2020–2039)

Scenario	**Parameter**	**20–23**(% Mean/Std)			**24–29**(% Mean/Std)			**30–39**(% Mean/Std)		
		Loganair	Delta	Cathay	Loganair	Delta	Cathay	Loganair	Delta	Cathay
A	Passenger	3/2	4/3	3.5/3	3/2	4/3	3.5/3	2/2	3/2	2.5/2
	Cargo	5/4	7/5	8/5	5/4	7/5	8/5	3/3	4/3	4/3
	Oil Price	5/20	5/20	5/20	5/20	5/20	5/20	2/15	2/15	2/15
	Discount Rate	1/2	1/3	1/2	1/2	1/3	1/2	0.5/2	0.5/2	0.5/2
B	Passenger	6/3	8/4	7/4	6/3	8/4	7/4	3/2	4/2	3.5/2
	Cargo	2/3	3/4	3.5/4	2/3	3/4	3.5/4	1/3	2/3	2/3
	Oil Price	4/20	4/20	4/20	4/20	4/20	4/20	2/15	2/15	2/15
	Discount Rate	1/2	1/3	1/2	1/2	1/3	1/2	0.5/2	0.5/2	0.5/2
C	Passenger	-30/10	-40/12	-35/12	10/10	15/12	12/12	3/2	4/2	3.5/2
	Cargo	-5/8	-10/10	-7/10	5/8	7/10	7/10	2/3	3/3	3/3
	Oil Price	-20/30	-20/30	-20/30	5/20	5/20	5/20	2/15	2/15	2/15
	Discount Rate	3/5	3/6	3/5	1/5	1/6	1/5	0.5/2	0.5/2	0.5/2

Each cell reports the mean and standard deviation of the normal distribution used to generate the corresponding parameter. All generated data are expressed as percentages.

Table 6.7 illustrates the evolving parameters for each trend within different scenario types.

Table 6.7: The Trend of Parameters which Varies in Three Different Scenarios.

Demand type	Scenario A	Scenario B	Scenario C
Passenger	—	$\uparrow$	$\downarrow\uparrow$
Cargo	$\uparrow$	—	$\downarrow\uparrow$
Oil Price	$\uparrow$	$\uparrow$	$\downarrow\uparrow$
Discount Rate	—	—	$\uparrow$—

— represents that the parameter beyond the decision phase remains stable. $\uparrow$ represents that the parameter beyond the decision phase with an increment trend. $\downarrow$ represents that the parameter beyond the decision phase with an decrement trend. $\downarrow\uparrow$ represents that the trend initially decreases and then slowly recovers. $\uparrow$— represents that the trend initially increases and then stay stable.

6.3.2 Impact of Budget

In the first set of sensitivity analysis, we consider the impact of different budget. We incrementally increase the airline's budget for each period in every scenario. We conducted the sensitivity over different types of airlines and the results are displayed in the Sections 6.3.2.1–6.3.2.3. To exclude the impact of the maximum debt and the environmental cost in the first set of sensitivity analysis, we set the value of maximum unpaid debt and environmental cost at 2,000,000 and 0.39 USD per gallon respectively. For the columns of table shown in sensitivity analysis, DS represents the scenario type. BD represents the budget constraint of the airline, measured in million USD. DB represents the maximum allowable unpaid debt in each period of the airline, measured in million USD. EP represents the environmental cost of consuming per gallon fuel, measured in USD.

6.3.2.1 Small Airlines

For small airlines, we've set the variable range of the maximum budget from 100 to 200 million USD. In each experiment, we increment this variable by 20 million USD. The resulting experimental data is presented in the Table 6.8. Column DS represents the type of scenario.

Table 6.8: Results of Sensitivity Analysis on the Maximum Budget of Small Airlines.

Index	AT	DS	BD	Gap(%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	S	A	100	0.06	969.25	0.0	0.0	137.0	0.0	30.0	0.0	0.0	0.0	0.0
2	S	A	120	0.0	1022.92	0.0	0.0	137.0	0.0	37.0	0.0	0.0	0.0	0.0
3	S	A	140	0.07	1066.27	0.0	0.0	137.0	0.0	45.0	0.0	0.0	0.0	0.0
4	S	A	160	0.06	1099.53	0.0	0.0	137.0	0.0	52.0	0.0	0.0	0.0	0.0
5	S	A	180	0.09	1112.33	0.0	0.0	137.0	0.0	55.0	0.0	0.0	0.0	0.0
6	S	A	200	0.0	1114.56	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
-	S	AVG	150.0	0.05	1064.14	0.0	0.0	137.0	0.0	45.83	0.0	0.0	0.0	0.0
7	S	B	100	0.1	971.83	0.0	0.0	137.0	0.0	30.0	0.0	0.0	0.0	0.0
8	S	B	120	0.07	1026	0.0	0.0	137.0	0.0	37.0	0.0	0.0	0.0	0.0
9	S	B	140	0.05	1075.10	0.0	0.0	137.0	0.0	46.0	0.0	0.0	0.0	0.0
10	S	B	160	0.0	1104.37	0.0	0.0	137.0	0.0	52.0	0.0	0.0	0.0	0.0
11	S	B	180	0.09	1117.28	0.0	0.0	137.0	0.0	55.0	0.0	0.0	0.0	0.0
12	S	B	200	0.0	1119.19	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
-	S	AVG	150.0	0.05	1068.96	0.0	0.0	137.0	0.0	46.0	0.0	0.0	0.0	0.0
13	S	C	100	0.0	984.87	0.0	0.0	137.0	0.0	31.0	0.0	0.0	0.0	0.0
14	S	C	120	0.08	1037.60	0.0	0.0	137.0	0.0	38.0	0.0	0.0	0.0	0.0
15	S	C	140	0.09	1073.43	0.0	0.0	137.0	0.0	44.0	0.0	0.0	0.0	0.0
16	S	C	160	0.1	1095.65	0.0	0.0	137.0	0.0	49.0	0.0	0.0	0.0	0.0
17	S	C	180	0.09	1101.46	0.0	0.0	137.0	0.0	52.0	0.0	0.0	0.0	0.0
18	S	C	200	0.09	1101.37	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
-	S	AVG	150.0	0.07	1065.73	0.0	0.0	137.0	0.0	44.17	0.0	0.0	0.0	0.0

Table 6.8 demonstrates how fleet management for small airlines changes with variations in their maximum budget. From Figure 6.1, we observe a clear trend: as the maximum budget increases, the airline's operating revenue also rises in the scenario A, B and C. This positive correlation is intuitive, as a larger budget enables the airlines to acquire more aircraft, thereby increasing its capacity to generate revenue. However, there's a critical point where this trend plateaus. Once the existing demand is fully met, further increases in the budget do not lead to a corresponding increase in revenue. This indicates a saturation point where additional aircraft no longer contribute to higher earnings due to market demand limitations.

From Table 6.8, we can clearly discern the dominant role of operating leases for small regional airlines, which is consistent with both our numerical experimental results in the Table 6.3 and real-world industry practices. In Figure 6.1, we observe an interesting phenomenon: in Scenario C, even when faced with a decline in demand (e.g., due to a pandemic), the revenue of regional airlines is not much lower than other two scenarios. We attribute this to the following factors: a significant decrease in oil prices caused by the pandemic, leading to reduced expenditures for regional airlines, and the relatively smaller impact of the pandemic-induced demand drop on regional airlines' already modest demand.

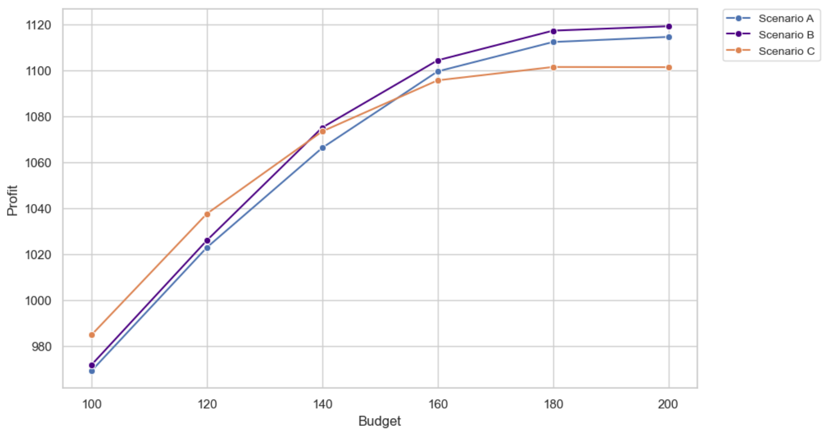

Figure 6.1: Sensitivity Analysis of Profit and Budget Under Different Scenarios with Different Budget Constraints of Small Airlines.

6.3.2.2 Medium Airlines

For medium airlines, we've set the variable range of the maximum budget from 10,000 to 35,000 million USD. In each experiment, we increment this variable by 5,000 million USD. The resulting experimental data is presented in the Table 6.9.

Table 6.9: Results of Sensitivity Analysis on the Maximum Budget of Medium Airlines

Index	AT	DS	BD	Gap (%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	M	A	10000	0.1	178800.46	37.0	39.0	374.0	37.0	362.0	18.0	0.0	0.0	2.0
2	M	A	15000	0.09	194311.02	83.0	39.0	374.0	83.0	304.0	18.0	0.0	0.0	2.0
3	M	A	20000	0.1	202527.20	128.0	39.0	374.0	128.0	266.0	18.0	0.0	0.0	2.0
4	M	A	25000	0.07	208998.09	171.0	40.0	371.0	171.0	240.0	16.0	0.0	0.0	5.0
5	M	A	30000	0.09	210060.15	181.0	41.0	376.0	181.0	231.0	18.0	0.0	0.0	0.0
6	M	A	35000	0.09	210060.15	181.0	41.0	376.0	181.0	231.0	18.0	0.0	0.0	0.0
-	M	AVG	22500	0.09	200792.84	130.17	39.83	374.17	130.17	272.33	17.67	0.0	0.0	1.83
7	M	B	10000	0.14	151650.71	55.0	25.0	375.0	55.0	364.0	18.0	0.0	0.0	1.0
8	M	B	15000	0.12	165065.20	102.0	23.0	374.0	102.0	292.0	18.0	0.0	0.0	2.0
9	M	B	20000	0.1	173978.46	150.0	20.0	374.0	150.0	252.0	18.0	0.0	0.0	2.0
10	M	B	25000	0.08	179512.44	194.0	20.0	374.0	194.0	233.0	18.0	0.0	0.0	2.0
11	M	B	30000	0.09	180051.18	205.0	20.0	376.0	205.0	232.0	18.0	0.0	0.0	0.0
12	M	B	35000	0.1	180041.94	205.0	20.0	375.0	205.0	231.0	18.0	0.0	0.0	1.0
-	M	AVG	22500	0.1	171716.65	151.83	21.33	374.67	151.83	267.33	18.0	0.0	0.0	1.33
13	M	C	10000	0.09	152770.43	48.0	18.0	365.0	48.0	289.0	15.0	0.0	0.0	11.0
14	M	C	15000	0.1	152871.79	49.0	18.0	366.0	49.0	292.0	14.0	0.0	0.0	10.0
15	M	C	20000	0.1	152873.85	49.0	18.0	365.0	49.0	290.0	14.0	0.0	0.0	11.0
16	M	C	25000	0.09	152885.24	49.0	18.0	365.0	49.0	289.0	15.0	0.0	0.0	11.0
17	M	C	30000	0.1	152872.05	49.0	18.0	365.0	49.0	289.0	14.0	0.0	0.0	11.0
18	M	C	35000	0.1	152875.96	49.0	19.0	366.0	49.0	288.0	15.0	0.0	0.0	10.0
-	M	AVG	22500	0.1	152858.22	48.83	18.17	365.33	48.83	289.5	14.5	0.0	0.0	10.67

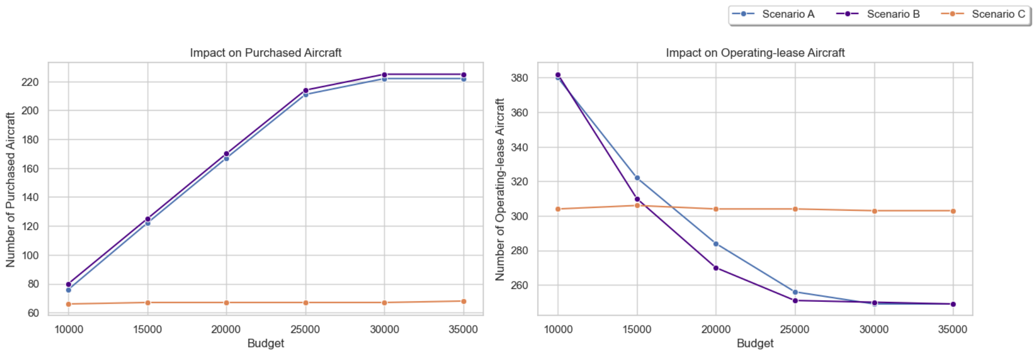

Figure 6.2: Different Fleet Management Strategies of Medium Airlines Under Different Budget Constraints.

Table 6.9 demonstrates how fleet management for medium airlines changes with variations in their maximum budget. We observe a similar trend of the profit and the budget to that of small airlines; however, due to the larger scale and greater demand base of mid-sized airlines, the profitability in Scenario C is significantly lower than in Scenarios A and B. We find out that in scenario C, the medium airlines are recommended to consider converting passenger aircraft to cargo planes. This recommendation stems from two key factors: Firstly, medium airlines often have a greater focus on cargo demand, which can become a more stable or even growing revenue stream during periods of passenger travel disruption. Secondly, the recovery of air freight demand after a sudden event like a pandemic tends to be more robust and swifter, making the conversion of aircraft a favorable strategy for the airline's long-term profitability and operational resilience.

We use Figure 6.2 to illustrate the different fleet management policies adopted under various scenarios and budget constraints. Figure 6.2 reveals a trend that the number of operating lease aircraft is lower when the budget is sufficient, while the number of purchased aircraft is higher in scenarios A and B. This indicates that, when facing tight budget constraints, airlines tend to prioritize immediate profit and revenue. Operating leases, which generally require lower periodic payments compared with outright purchases, are therefore more suitable for airlines' financial management under such conditions. Within the sensitivity analysis range, the policies of airlines in scenario C remain unchanged, as the budget constraints within this range are sufficient to meet all demand in scenario C. As a result, no significant changes are observed in the chart for this scenario in the Figure 6.2.

6.3.2.3 Large Airlines

For large airlines, we've set the variable range of the maximum budget from 40,000 to 115,000 million USD. In each experiment, we increment this variable by 15000 million USD. The resulting experimental data is presented in the Table 6.10.

Table 6.10: Results of Sensitivity Analysis on the Maximum Budget of Large Airlines.

Index	AT	DS	BD	Gap (%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	L	A	40000	0.02	597343.76	715.0	0.0	376.0	715.0	2984.0	0.0	0.0	0.0	0.0
2	L	A	55000	0.0	639901.42	983.0	0.0	376.0	983.0	2906.0	0.0	0.0	0.0	0.0
3	L	A	70000	0.0	651205.13	1251.0	0.0	376.0	1251.0	2651.0	0.0	0.0	0.0	0.0
4	L	A	85000	0.01	656998.45	1520.0	0.0	376.0	1520.0	2386.0	0.0	0.0	0.0	0.0
5	L	A	100000	0.0	659477.02	1673.0	0.0	376.0	1673.0	2301.0	0.0	0.0	0.0	0.0
6	L	A	115000	0.0	659477.02	1673.0	0.0	376.0	1673.0	2301.0	0.0	0.0	0.0	0.0
-	L	AVG	77500	0.01	644067.13	1302.5	0.0	376.0	1302.5	2588.17	0.0	0.0	0.0	0.0
7	L	B	40000	0.01	550859.37	640.0	0.0	376.0	640.0	3110.0	0.0	0.0	0.0	0.0
8	L	B	55000	0.0	582823.96	881.0	0.0	376.0	881.0	3078.0	0.0	0.0	0.0	0.0
9	L	B	70000	0.0	595822.99	1120.0	0.0	376.0	1120.0	2961.0	0.0	0.0	0.0	0.0
10	L	B	85000	0.0	598334.81	1404.0	0.0	376.0	1404.0	2709.0	0.0	0.0	0.0	0.0
11	L	B	100000	0.0	598923.24	1645.0	0.0	376.0	1645.0	2468.0	0.0	0.0	0.0	0.0
12	L	B	115000	0.0	599332.50	1813.0	0.0	376.0	1813.0	2301.0	0.0	0.0	0.0	0.0
-	L	AVG	77500	0.0	587682.81	1250.5	0.0	376.0	1250.5	2771.17	0.0	0.0	0.0	0.0
13	L	C	40000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
14	L	C	55000	0.0	400756.87	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
15	L	C	70000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
16	L	C	85000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
17	L	C	100000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
18	L	C	115000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
-	L	AVG	77500	0.01	400748.37	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0

Table 6.10 demonstrates how fleet management for large airlines changes with variations in their maximum budget. We can observe a similar trend to that of small and and mid-sized airlines in the relationship between profit and budget. The trends in the number of purchased and leased aircraft with budget variations are also consistent with those of mid-sized airlines. This similarity reflects the

dominant role of operating leases in addressing short-term demand. Additionally, we find that large airlines focused on passenger demand do not opt for P2F aircraft. This is because large airlines do not have a particularly high demand for dedicated cargo operations, and their substantial passenger aircraft can meet most cargo demand through belly capacity. making P2F an suboptimal choice for such airlines.

6.3.3 Impact of Maximum Allowable Unpaid Debt

In the second set of sensitivity analysis, we consider the impact of maximum allowable unpaid debt. We incrementally increase the airline's maximum allowable unpaid debt for each period in every scenario. We conducted the sensitivity over different types of airlines and the results are displayed in the Sections 6.3.3.1–6.3.3.3. To exclude the impact of the debt and the environmental cost, we set the value of maximum debt and environmental cost at 2,000,000 million USD and 0.39 USD per gallon respectively.

6.3.3.1 Small Airlines

We set the range of the maximum allowable unpaid budget for small airlines from 20 to 120 million USD, increasing it by 20 million USD in each experiment. The resulting data are presented in Table 6.11.

Table 6.11: Results of Sensitivity Analysis on the Maximum Allowable Unpaid Budget of Small Airlines.

Index	AT	DS	DB	Gap(%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	S	A	20	0.0	773.83	0.0	0.0	137.0	0.0	30.0	0.0	0.0	0.0	0.0
2	S	A	40	0.0	1086.89	0.0	0.0	137.0	0.0	50.0	0.0	0.0	0.0	0.0
3	S	A	60	0.01	1114.24	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
4	S	A	80	0.0	1114.56	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
5	S	A	100	0.0	1114.56	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
6	S	A	120	0.02	1114.56	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
-	S	AVG	70.0	0.01	1053.11	0.0	0.0	137.0	0.0	50.67	0.0	0.0	0.0	0.0
7	S	B	20	0.0	775.56	0.0	0.0	137.0	0.0	30.0	0.0	0.0	0.0	0.0
8	S	B	40	0.09	1090.22	0.0	0.0	137.0	0.0	50.0	0.0	0.0	0.0	0.0
9	S	B	60	0.01	1118.62	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
10	S	B	80	0.0	1119.19	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
11	S	B	100	0.0	1119.19	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
12	S	B	120	0.0	1119.19	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
-	S	AVG	70.0	0.02	1057.0	0.0	0.0	137.0	0.0	50.67	0.0	0.0	0.0	0.0
13	S	C	20	0.08	779.44	0.0	0.0	137.0	0.0	30.0	0.0	0.0	0.0	0.0
14	S	C	40	0.07	1096.95	0.0	0.0	137.0	0.0	50.0	0.0	0.0	0.0	0.0
15	S	C	60	0.09	1101.37	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
16	S	C	80	0.09	1101.37	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
17	S	C	100	0.09	1101.37	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
18	S	C	120	0.09	1101.37	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
-	S	AVG	70.0	0.09	1046.98	0.0	0.0	137.0	0.0	47.33	0.0	0.0	0.0	0.0

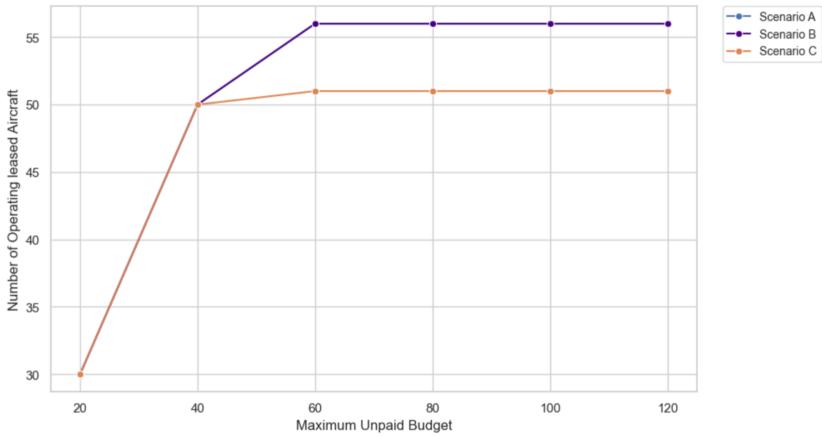

Figure 6.3: Different Fleet Management Strategies of Small Airlines Under Different Maximum Unpaid Debt Constraints.

Table 6.11 illustrates the influence of maximum unpaid debt on a regional airline's fleet management. We can observe that regardless of the maximum unpaid debt level, the core fleet management policy doesn't change drastically. This intuitively reflects the relatively straightforward management approach typically adopted by regional airlines. Interestingly, when the maximum unpaid debt increases, there's a tendency for the number of aircraft under operating leases to rise, as shown in Figure 6.3. It can be explained that operating lease allows the airline to concentrate on its core operations rather than the complexities of asset management, which is vital for the simple fleet management of small airlines.

6.3.3.2 Medium Airlines

For medium airlines, we've set the variable range of the maximum allowable unpaid budget from 3000 to 28,000 million USD. In each experiment, we increment this variable by 5000 million USD. The resulting experimental data is presented in the Table 6.12.

Table 6.12: Results of Sensitivity Analysis on the Maximum Allowable Unpaid Budget of Medium Airlines.

Index	AT	DS	BD	Gap (%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	M	A	3000	0.09	136393.83	0.0	20.0	366.0	0.0	495.0	1.0	0.0	7.0	10.0
2	M	A	8000	0.09	184420.56	140.0	16.0	366.0	140.0	118.0	0.0	0.0	9.0	10.0
3	M	A	13000	0.09	203721.88	150.0	27.0	365.0	150.0	233.0	9.0	0.0	0.0	11.0
4	M	A	18000	0.08	207968.89	166.0	35.0	368.0	166.0	242.0	15.0	0.0	0.0	8.0
5	M	A	23000	0.09	208931.08	173.0	35.0	369.0	173.0	239.0	15.0	0.0	0.0	7.0
6	M	A	28000	0.09	209920.97	179.0	36.0	369.0	179.0	239.0	15.0	0.0	0.0	7.0
-	M	AVG	15500.0	0.09	191892.87	134.67	28.17	367.17	134.67	261.0	9.17	0.0	2.67	8.83
7	M	B	3000	0.1	127581.21	16.0	14.0	366.0	16.0	488.0	3.0	0.0	5.0	10.0
8	M	B	8000	0.09	162143.06	152.0	11.0	365.0	152.0	155.0	9.0	0.0	0.0	11.0
9	M	B	13000	0.09	176154.93	171.0	12.0	365.0	171.0	241.0	11.0	0.0	0.0	11.0
10	M	B	18000	0.1	177798.33	187.0	19.0	375.0	187.0	234.0	18.0	0.0	0.0	1.0
11	M	B	23000	0.1	178823.72	192.0	19.0	374.0	192.0	235.0	17.0	0.0	0.0	2.0
12	M	B	28000	0.1	179850.97	199.0	20.0	376.0	199.0	232.0	18.0	0.0	0.0	0.0
-	M	AVG	15500.0	0.1	167058.70	152.83	15.83	370.17	152.83	264.17	12.67	0.0	0.83	5.83
13	M	C	3000	0.1	140822.49	30.0	6.0	366.0	30.0	479.0	4.0	0.0	5.0	10.0
14	M	C	8000	0.09	152664.62	47.0	18.0	365.0	47.0	291.0	14.0	0.0	0.0	11.0
15	M	C	13000	0.08	152907.87	49.0	19.0	366.0	49.0	290.0	15.0	0.0	0.0	10.0
16	M	C	18000	0.08	152903.85	49.0	19.0	366.0	49.0	290.0	15.0	0.0	0.0	10.0
17	M	C	23000	0.09	152895.96	49.0	19.0	366.0	49.0	291.0	15.0	0.0	0.0	10.0
18	M	C	28000	0.08	152894.84	49.0	19.0	366.0	49.0	291.0	15.0	0.0	0.0	10.0
-	M	AVG	15500.0	0.09	150848.27	45.5	16.67	365.83	45.5	322.0	13.0	0.0	0.83	10.17

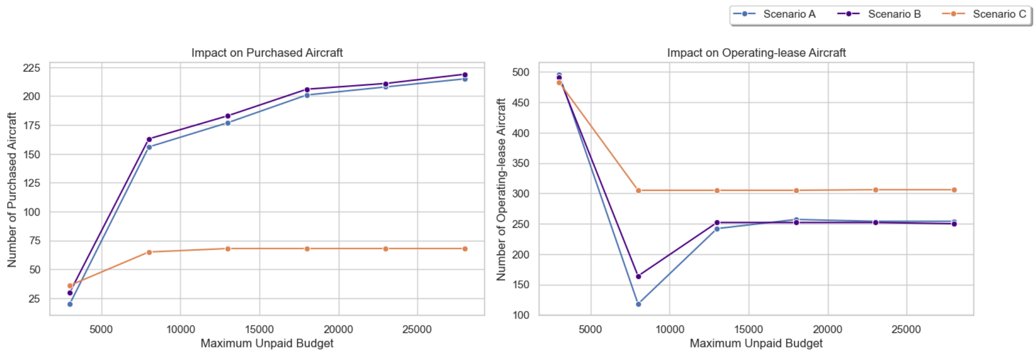

Figure 6.4: Different Fleet Management Strategies of Medium Airlines Under Different Maximum Unpaid Debt Constraints.

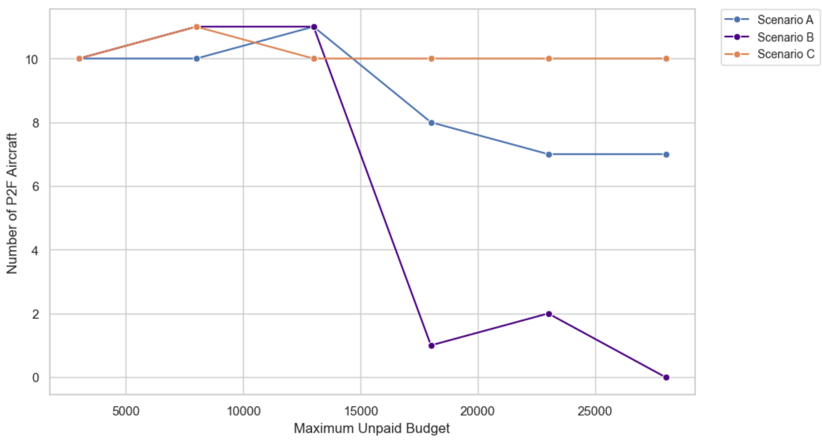

Figure 6.5: Different P2F Aircraft Number of Medium Airlines Under Different Maximum Unpaid Debt Constraints.

Table 6.12 illustrates the influence of maximum unpaid debt on the medium airlines' fleet management. It can be observed that purchasing aircraft and operating leased aircraft are both significant for medium airlines. As the maximum unpaid debt increases, the number of operating leased aircraft decreases. This is because the long-term return rate of purchasing aircraft is superior to that of operating leases, leading airlines to prefer purchasing more aircraft when financial risk decreases. Figure 6.4 shows the trend of the number of purchased aircraft and leased aircraft as the maximum unpaid debt increases. Additionally, as shown in Figure 6.5, the number of P2F aircraft is closely related to the airline's maximum unpaid debt. This is due to the significantly lower cost of P2F aircraft compared with purchasing or leasing dedicated freighters, allowing airlines to effectively reduce financial risk by opting for P2F aircraft.

6.3.3.3 Large Airlines

For large airlines, we've set the variable range of the maximum allowable unpaid budget from 30,000 to 40,000 million USD. In each experiment, we increment this variable by 2000 million USD. The resulting experimental data is presented in the Table 6.13.

Table 6.13: Results of Sensitivity Analysis on the Maximum Allowable Unpaid Budget of Large Airlines.

Index	AT	DS	BD	Gap (%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	L	A	30000	0.04	359571.16	207.0	0.0	351.0	232.0	2799.0	0.0	0.0	0.0	15.0
2	L	A	32000	0.01	448775.33	568.0	0.0	366.0	578.0	2307.0	0.0	0.0	0.0	0.0
3	L	A	34000	0.0	509117.81	700.0	0.0	376.0	700.0	2884.0	0.0	0.0	0.0	0.0
4	L	A	36000	0.0	564154.79	1027.0	0.0	376.0	1027.0	2556.0	0.0	0.0	0.0	0.0
5	L	A	38000	0.0	617293.25	1333.0	0.0	376.0	1333.0	2259.0	0.0	0.0	0.0	0.0
6	L	A	40000	0.0	654309.07	1529.0	0.0	376.0	1529.0	2301.0	0.0	0.0	0.0	0.0
-	L	AVG	35000.0	0.01	525536.90	894.0	0.0	370.17	899.83	2517.67	0.0	0.0	0.0	2.5
7	L	B	30000	0.07	350531.09	207.0	0.0	357.0	226.0	2891.0	0.0	0.0	0.0	9.0
8	L	B	32000	0.0	421814.03	407.0	0.0	376.0	407.0	3176.0	0.0	0.0	0.0	0.0
9	L	B	34000	0.0	466797.58	703.0	0.0	376.0	703.0	2881.0	0.0	0.0	0.0	0.0
10	L	B	36000	0.0	509019.13	1056.0	0.0	376.0	1056.0	2528.0	0.0	0.0	0.0	0.0
11	L	B	38000	0.0	550609.64	1327.0	0.0	376.0	1327.0	2267.0	0.0	0.0	0.0	0.0
12	L	B	40000	0.01	585448.58	1529.0	0.0	376.0	1529.0	2300.0	0.0	0.0	0.0	0.0
-	L	AVG	35000.0	0.01	480703.34	871.5	0.0	372.83	874.67	2673.83	0.0	0.0	0.0	1.5
13	L	C	30000	0.02	372304.48	196.0	0.0	373.0	199.0	2861.0	0.0	0.0	0.0	3.0
14	L	C	32000	0.01	400210.47	282.0	0.0	376.0	282.0	2854.0	0.0	0.0	0.0	0.0
15	L	C	34000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
16	L	C	36000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
17	L	C	38000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
18	L	C	40000	0.01	400746.67	247.0	0.0	376.0	247.0	2860.0	0.0	0.0	0.0	0.0
-	L	AVG	35000.0	0.01	395916.94	244.33	0.0	375.5	244.83	2859.17	0.0	0.0	0.0	0.5

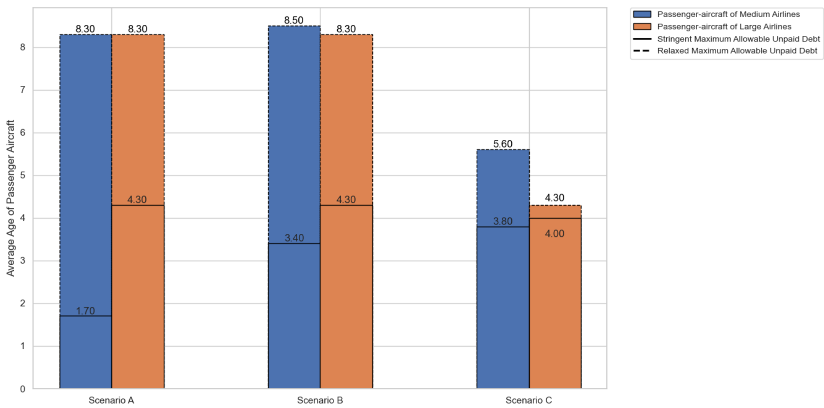

Figure 6.6: Average Age of Passenger Aircraft of Medium and Large Airlines Under Different Maximum Allowable Unpaid Debt Constraints.

Table 6.13 illustrates the influence of maximum unpaid debt on the large airlines' fleet management. The data in the table once again confirms that operating leases can effectively reduce the financial risk of airlines. However, purchasing aircraft is a recommended long-term investment option when financial conditions are more favorable.

We simultaneously examined the impact of different maximum allowable unpaid debt levels on the average operating aircraft age of airlines under various scenarios. Figure 6.6 presents bar charts illustrating how the average fleet age of medium-sized and large airlines changes with varying levels of allowable unpaid debt. The solid lines represent the average fleet age when airlines operate under a stringent maximum unpaid debt constraint, while the dashed lines represent the corresponding values under more relaxed debt conditions. We observe that when the maximum allowable unpaid debt is relatively low, airlines tend to prefer short-term leasing of aircraft. Although this strategy may not fully satisfy long-term demand, it results in a lower average operating age for the fleet. As the maximum allowable unpaid debt increases, airlines are more inclined to purchase aircraft to meet long-term demand, which leads to an increase in the average operating age of their fleets.

This trend also varies across different scenarios. In particular, under scenario C, which represents the special case of a pandemic, we find that even when airlines have sufficient maximum allowable unpaid debt, the fluctuations in average operating aircraft age remain relatively small. This is because scenario C is characterized by a declining trend in future demand, which reduces airlines' incentives to make long-term investments.

6.3.4 Impact of Environmental Cost

In the final set of sensitivity analyses, we examine the impact of environmental cost. For each airline type and each scenario, we incrementally increase the environmental cost from 0.05 to 2.00 USD per gallon in steps of 0.39 USD per gallon. The sensitivity analyses are conducted for different types of airlines, and the results are presented in Sections 6.3.4.1–6.3.4.3. To exclude the influence of budget and maximum unpaid debt, we set both values to 2,000,000 million USD.

6.3.4.1 Small Airlines

Table 6.14 demonstrates the influence of environmental cost on the fleet management of small airlines. We find that, regardless of the scenario, the airline's strategy does not undergo significant changes. This can be explained by the fact that regional airlines, when financial constraints are not a primary concern, predominantly rely on leasing new aircraft. Consequently, with a younger fleet, their strategies are less affected by changes in environmental cost.

Table 6.14: Results of Sensitivity Analysis on the Environmental Policy of Small Airlines.

Index	AT	DS	BD	Gap (%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	S	A	0.05	0.0	1,135.29	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
2	S	A	0.44	0.0	1,111.51	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
3	S	A	0.83	0.0	1,087.73	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
4	S	A	1.22	0.03	1,063.96	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
5	S	A	1.61	0.01	1,040.28	0.0	0.0	137.0	0.0	55.0	0.0	0.0	0.0	0.0
6	S	A	2.0	0.04	1,016.92	0.0	0.0	137.0	0.0	55.0	0.0	0.0	0.0	0.0
-	S	AVG	1.23	0.01	1,075.95	0.0	0.0	137.0	0.0	55.67	0.0	0.0	0.0	0.0
7	S	B	0.05	0.0	1,139.92	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
8	S	B	0.44	0.0	1,116.14	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
9	S	B	0.83	0.0	1,092.37	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
10	S	B	1.22	0.0	1,068.59	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
11	S	B	1.61	0.0	1,044.81	0.0	0.0	137.0	0.0	56.0	0.0	0.0	0.0	0.0
12	S	B	2.0	0.0	1,021.26	0.0	0.0	137.0	0.0	55.0	0.0	0.0	0.0	0.0
-	S	AVG	1.23	0.0	1,080.52	0.0	0.0	137.0	0.0	55.83	0.0	0.0	0.0	0.0
13	S	C	0.05	0.09	1,120.73	0.0	0.0	137.0	0.0	52.0	0.0	0.0	0.0	0.0
14	S	C	0.44	0.09	1,098.60	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
15	S	C	0.83	0.08	1,076.92	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
16	S	C	1.22	0.07	1,055.24	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
17	S	C	1.61	0.01	1,033.56	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0
18	S	C	2.0	0.07	1,012.01	0.0	0.0	137.0	0.0	50.0	0.0	0.0	0.0	0.0
-	S	AVG	1.23	0.07	1,066.18	0.0	0.0	137.0	0.0	51.0	0.0	0.0	0.0	0.0

6.3.4.2 Medium Airlines

Table 6.15 demonstrates the influence of environmental cost on the fleet management of medium-sized airlines. With increasingly stringent environmental cost, the operational profits of airlines decrease across all scenarios. Figure 6.7 shows the trends in the number of purchased and leased aircraft as the environmental cost increases. Airlines in all scenarios become more inclined to lease aircraft to cope with stricter environmental penalties, as leasing enables them to effectively lower the average operating age of their fleet and thereby mitigate the impact of these penalties. Additionally, as shown in Figure 6.8, the number of P2F aircraft is closely related to the environmental cost level in scenario C. Airlines tend to reduce the number of P2F aircraft, as these are typically older and would incur more environmental cost under stricter environmental policies.

Table 6.15: Results of Sensitivity Analysis on the Environmental Policy of Medium Airlines.

Index	AT	DS	BD	Gap (%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	M	A	0.05	0.09	223,265.58	185.0	43.0	376.0	185.0	231.0	19.0	0.0	0.0	0.0
2	M	A	0.44	0.1	208,124.33	180.0	41.0	376.0	180.0	231.0	19.0	0.0	0.0	0.0
3	M	A	0.83	0.1	193,314.45	173.0	40.0	376.0	173.0	236.0	18.0	0.0	0.0	0.0
4	M	A	1.22	0.05	179,109.36	170.0	39.0	376.0	170.0	396.0	19.0	0.0	0.0	0.0
5	M	A	1.61	0.05	165,183.53	166.0	38.0	376.0	166.0	421.0	19.0	0.0	0.0	0.0
6	M	A	2.0	0.07	151,693.26	162.0	36.0	376.0	162.0	583.0	20.0	0.0	0.0	0.0
-	M	AVG	1.23	0.08	186,781.75	172.67	39.5	376.0	172.67	349.67	19.0	0.0	0.0	0.0
7	M	B	0.05	0.1	192,947.74	211.0	20.0	376.0	211.0	231.0	18.0	0.0	0.0	0.0
8	M	B	0.44	0.1	178,160.38	203.0	20.0	375.0	203.0	234.0	18.0	0.0	0.0	1.0
9	M	B	0.83	0.08	163,741.25	194.0	20.0	375.0	194.0	259.0	18.0	0.0	0.0	1.0
10	M	B	1.22	0.06	149,937.05	187.0	20.0	376.0	187.0	396.0	19.0	0.0	0.0	0.0
11	M	B	1.61	0.06	136,630.02	174.0	20.0	376.0	174.0	421.0	19.0	0.0	0.0	0.0
12	M	B	2.0	0.09	124,013.46	168.0	20.0	376.0	168.0	584.0	20.0	0.0	0.0	0.0
-	M	AVG	1.23	0.08	157,571.65	189.5	20.0	375.67	189.5	354.17	18.67	0.0	0.0	0.33
13	M	C	0.05	0.09	159,632.88	51.0	19.0	365.0	51.0	289.0	14.0	0.0	0.0	11.0
14	M	C	0.44	0.07	151,936.14	49.0	19.0	366.0	49.0	292.0	15.0	0.0	0.0	10.0
15	M	C	0.83	0.09	144,286.55	48.0	18.0	365.0	48.0	318.0	14.0	0.0	0.0	11.0
16	M	C	1.22	0.09	137,046.45	46.0	20.0	369.0	46.0	555.0	19.0	0.0	0.0	7.0
17	M	C	1.61	0.09	129,976.76	44.0	20.0	369.0	44.0	591.0	17.0	0.0	0.0	7.0
18	M	C	2.0	0.08	123,085	42.0	23.0	374.0	42.0	690.0	20.0	0.0	0.0	2.0
-	M	AVG	1.23	0.08	140,993.96	46.67	19.83	368.0	46.67	455.83	16.5	0.0	0.0	8.0

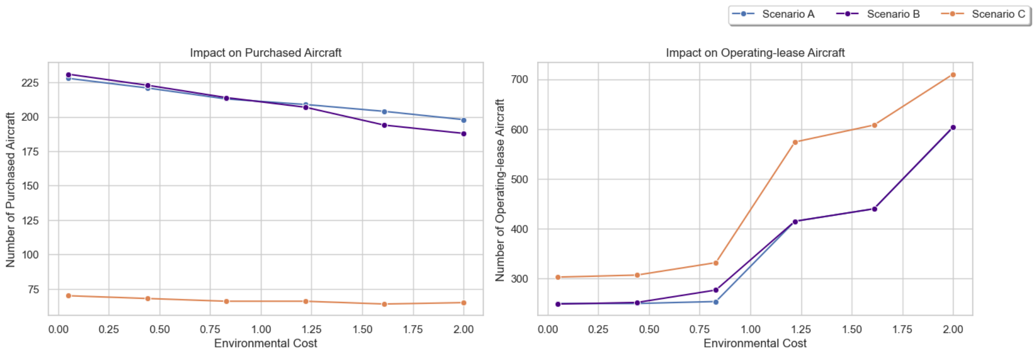

Figure 6.7: Different P2F Aircraft Number of Medium Airlines Under Different Environmental Cost Constraints.

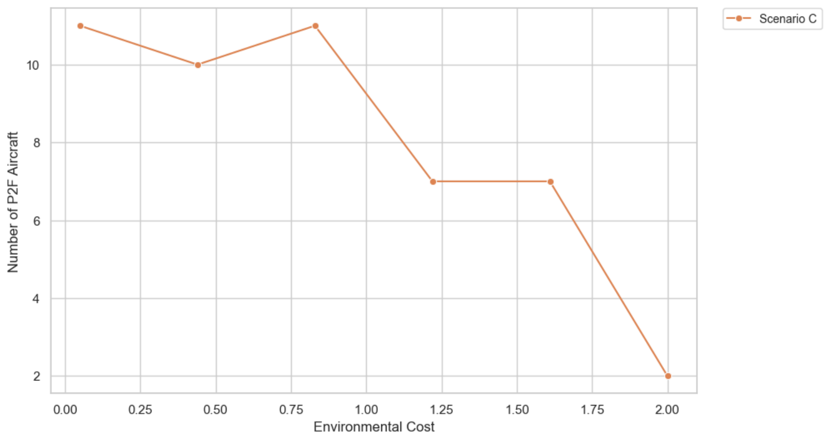

Figure 6.8: P2F Aircraft Number of Medium Airlines in Scenario C Under Different Environmental Cost Constraints.

6.3.4.3 Large Airlines

Table 6.16 demonstrates the influence of environmental policy on the fleet management of large airlines. The data in the table are consistent with the trends shown in Figure 6.7: across different scenarios, as the environmental cost for airline emissions increase, airlines show a greater preference for operating lease aircraft.

We also simultaneously examined the impact of different environmental cost levels on the average operating aircraft age of airlines under various scenarios. Figure 6.9 presents bar charts illustrating how the average fleet age of medium-sized and large airlines changes with varying levels of environmental cost. We observe that when the environmental cost is relatively low, airlines may be less motivated to update their fleets, potentially operating older aircraft. However, as the environmental cost increases, airlines are more inclined to utilize younger aircraft, since newer aircraft are more fuel-efficient and produce fewer greenhouse gas emissions, resulting in lower penalties and greater operational advantages. This effect becomes even more pronounced under stricter environmental policies.

We find that for large airlines under scenario C, the fluctuation in average aircraft age remains limited even as the environmental cost changes. This is because, in scenario C, large airlines primarily rely on operating leases for their fleet, even when the environmental cost is relatively low. As a result, the average age of their aircraft is already kept at a lower level, and further increases in the environmental cost do not significantly impact their fleet age.

Table 6.16: Results of Sensitivity Analysis on the Environmental Policy of Large Airlines.

Index	AT	DS	BD	Gap (%)	NPV	NP		NS	ND	NOL		NCL		NCF
						NPP	NPC			PNOL	FNOL	PNCL	FNCL	
1	L	A	0.05	0.0	696,341.24	1684.0	0.0	376.0	1684.0	2300.0	0.0	0.0	0.0	0.0
2	L	A	0.44	0.0	654,033.81	1673.0	0.0	376.0	1673.0	2300.0	0.0	0.0	0.0	0.0
3	L	A	0.83	0.0	613,725.13	1606.0	0.0	376.0	1606.0	2301.0	0.0	0.0	0.0	0.0
4	L	A	1.22	0.0	574,209.85	1580.0	0.0	376.0	1580.0	2301.0	0.0	0.0	0.0	0.0
5	L	A	1.61	0.0	537,693.97	804.0	0.0	376.0	804.0	3056.0	0.0	0.0	0.0	0.0
6	L	A	2.0	0.0	505,671.54	727.0	0.0	376.0	727.0	3122.0	0.0	0.0	0.0	0.0
-	L	AVG	1.23	0.0	596,945.92	1345.67	0.0	376.0	1345.67	2563.33	0.0	0.0	0.0	0.0
7	L	B	0.05	0.0	638,737.65	1830.0	0.0	376.0	1830.0	2301.0	0.0	0.0	0.0	0.0
8	L	B	0.44	0.0	593,602.27	1769.0	0.0	376.0	1769.0	2344.0	0.0	0.0	0.0	0.0
9	L	B	0.83	0.0	559,294.13	491.0	0.0	376.0	491.0	3592.0	0.0	0.0	0.0	0.0
10	L	B	1.22	0.0	528,542.59	449.0	0.0	376.0	449.0	3583.0	0.0	0.0	0.0	0.0
11	L	B	1.61	0.0	498,640.21	420.0	0.0	376.0	420.0	3603.0	0.0	0.0	0.0	0.0
12	L	B	2.0	0.0	469,112.50	398.0	0.0	376.0	398.0	3621.0	0.0	0.0	0.0	0.0
-	L	AVG	1.23	0.0	547,988.22	892.83	0.0	376.0	892.83	3174.0	0.0	0.0	0.0	0.0
13	L	C	0.05	0.01	416,202.38	253.0	0.0	376.0	253.0	2853.0	0.0	0.0	0.0	0.0
14	L	C	0.44	0.0	398,499.46	245.0	0.0	376.0	245.0	2863.0	0.0	0.0	0.0	0.0
15	L	C	0.83	0.0	382,494.58	291.0	0.0	376.0	291.0	2860.0	0.0	0.0	0.0	0.0
16	L	C	1.22	0.0	367,767.18	286.0	0.0	376.0	286.0	2859.0	0.0	0.0	0.0	0.0
17	L	C	1.61	0.0	353,155.39	282.0	0.0	376.0	282.0	2863.0	0.0	0.0	0.0	0.0
18	L	C	2.0	0.01	338,738.78	267.0	0.0	376.0	267.0	2878.0	0.0	0.0	0.0	0.0
-	L	AVG	1.23	0.0	376,142.96	270.67	0.0	376.0	270.67	2862.67	0.0	0.0	0.0	0.0

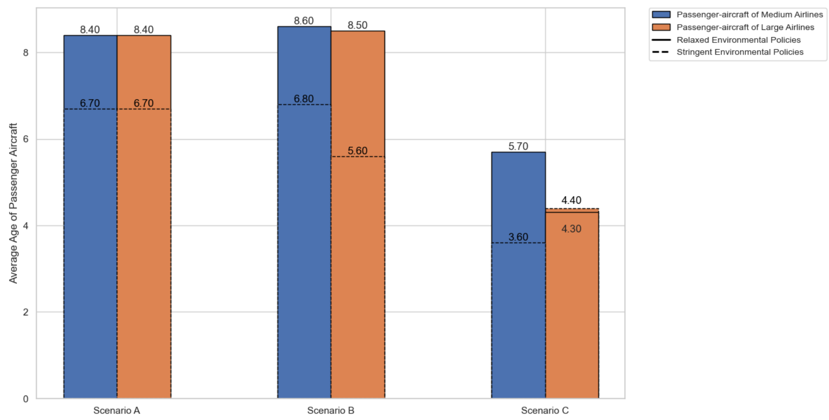

Figure 6.9: Average Age of Passenger Aircraft of Medium and Large Airlines Under Different Environmental Cost Constraints.

6.4 Discussion of Policy Implications

Our analysis highlights several key insights with direct policy implications for airline fleet management. In particular, the results underscore how certain fleet strategies can be supported or guided by regulatory and industry policy measures to improve overall resilience and sustainability in the aviation sector. Rather than treating policy considerations as an afterthought, we integrate them here with the discussion of our findings to emphasize how closely operational decisions and policy frameworks are intertwined in practice.

Promoting Flexible Fleet Capacity through Leasing: Operating leases play a critical role in fleet acquisition under conditions of demand uncertainty or tight budget constraints. In scenarios with volatile or unpredictable demand, our optimization found that airlines benefit from the flexibility of short-term leases, which allow rapid scaling of capacity without long-term capital commitment. Our results further reveal that operating leases are important for all three types of airlines considered. They are especially crucial for small regional airlines, as leasing provides the flexibility required for these carriers to manage limited resources and adapt to market fluctuations. For medium-sized airlines that need to address both passenger and cargo demand, leasing supports efficient fleet adjustment and capacity balancing. Even for large airlines primarily focused on passenger operations, leasing is valuable for fleet renewal and risk management. This finding suggests that policymakers should incentivize the use of operating leases as a tool for resilience. For example, tax relief or credits on leased aircraft, alongside streamlined regulations for lease agreements and supportive financing (e.g., government-backed low-interest loans), would lower the barriers for airlines to adopt leasing strategies. A notable existing measure is Hong Kong's tax concession scheme for qualifying aircraft lessors, where, as a compensation for the loss of depreciation allowances, a qualifying aircraft lessor is eligible for a 20% tax base concession shown in Department (2023). Such measures would enable carriers—particularly those with limited capital or serving volatile markets—to align fleet size with shifting demand. These recommendations are directly validated by our finding that operating leases tend to dominate optimal decisions in high-uncertainty scenarios, making a strong case for policy support of leasing as a means to enhance industry agility.

Highlighting the Impact of Budget Levels: Another important observation is the significant impact of annual budget levels on fleet management policies. Airlines with greater annual budgets can focus more on long-term investments and are able to purchase more aircraft, while those with tighter budgets tend to rely more on operating leases to achieve flexibility. This trend is present for all airline types, but is particularly pronounced for small regional and medium-sized carriers.

Closely related to this, the results underscore the long-term cost and efficiency advantage of operating newer, more fuel-efficient aircraft. The analysis showed that replacing aging jets with modern, fuel-efficient models can significantly reduce maintenance and fuel costs while also lowering emissions. This underscores the need for policies that accelerate fleet modernization and the adoption of greener aircraft. Policymakers could implement targeted subsidies or tax incentives to assist airlines in acquiring new-generation aircraft that have lower environmental footprints. In parallel, imposing gradually stricter penalties on continued operation of older, less efficient planes – for instance, via carbon taxes or higher operational fees for aging aircraft – would encourage airlines to retire or upgrade outdated fleets. Public investment in research and development of sustainable aviation technologies (e.g., electric or hybrid propulsion) can further support this transition. These policy measures align with our findings by reducing long-run operational costs and environmental impacts through fleet renewal, and they complement global efforts to meet stricter emissions regulations in aviation.

Facilitating P2F Conversions for Cargo Growth: Our study also finds that P2F conversions offer a strategic pathway to meet rising cargo demand without incurring excessive new debt. This is especially relevant for medium-sized airlines or those with significant cargo operations, particularly when facing large fluctuations in cargo demand. However, reliance on older aircraft for P2F conversion may negatively impact airlines' environmental performance and runs counter to sustainability objectives. Despite this, P2F conversion helps lower financial risk for airlines by avoiding large new capital investments. In scenarios reflecting robust e-commerce growth, converting older passenger aircraft into freighters emerged as a cost-effective strategy for expanding cargo capacity. This approach allows airlines to repurpose existing assets instead of purchasing additional freighters, thereby managing debt levels more prudently. To capitalize on these benefits at an industry level, regulatory bodies should simplify and expedite the certification process for P2F conversions, which can currently be complex and time-consuming. Simplified certification standards, coupled with tax incentives or grants to offset upfront conversion costs, would make it easier and more attractive for airlines to convert aircraft for cargo use. Furthermore, complementary investments in cargo infrastructure – for example, expanding warehousing and handling facilities at major airports, especially in emerging markets – would maximize the utility of the growing converted freighter fleet. Together, these policy actions would support the study's conclusion that P2F conversions help optimize cargo capacity under demand growth while controlling financial risk, ensuring that air cargo supply can keep pace with the fast-expanding e-commerce sector.

Maintaining Financial Stability and Managing Debt: A significant trade-off illuminated by our model is between fleet expansion for profitability and the accumulation of debt. While investing in owned aircraft (through purchases or long-term capital leases) can improve an airline's profit potential and control over assets, our results warn that excessive reliance on these capital-intensive strategies heightens financial vulnerability. At the same time, operating leases and P2F conversions can effectively reduce the airline's accumulated debt and help maintain a healthy financial position. Scenarios with aggressive fleet expansion via purchases showed higher debt loads, which could become unsustainable under adverse conditions (such as demand downturns or interest-rate spikes). This finding has clear policy relevance: policymakers and industry regulators should consider establishing guidelines or oversight mechanisms for airline leverage. For instance, introducing recommended debt-to-equity ratio limits or stress-testing requirements for airlines could help prevent over-leveraging in pursuit of growth. Regulatory oversight might also include requiring transparency in financial reporting of lease obligations and debt, enabling early intervention if risk levels grow too high. In addition, contingency measures at the policy level – such as crisis-specific liquidity support or emergency credit lines for airlines – could be put in place to stabilize the sector during major disruptions (e.g., sudden fuel price shocks or global pandemics). These steps are in line with our study's warnings: they would mitigate the financial risks associated with heavy debt burdens, ensuring that short-term fleet expansion does not compromise long-term industry stability.

Prioritizing Sustainability in Fleet Decisions: Environmental sustainability must be a guiding principle in future fleet management policies. Our analysis, while economically focused, incorporated factors such as maintenance costs and aircraft age that are closely linked to fuel efficiency and emissions; the findings reinforce the environmental benefits of retiring older, less efficient aircraft in favor of modern fleets. Notably, our results indicate that when airlines have ample budgets or strong financial resilience, particularly when pursuing long-term investments, they should pay special attention to managing the average age of their fleet, as this is directly related to sustainability performance. In light of environmental policies, choosing to operate newer aircraft through operating lease and adopting more flexible fleet management strategies are particularly beneficial for airline development, especially for carriers facing more stringent regulatory requirements. When airlines are confronted with high cargo demand, the potential environmental cost associated with P2F conversions becomes an important factor that must be considered in their decision-making. Policymakers should further promote sustainability by enacting stricter emissions standards for airline operations, effectively phasing out the most polluting and noisiest aircraft from fleets. Requiring major fleet decisions or expansion plans to undergo environmental and social impact assessments can help ensure broader community and climate impacts are addressed. Additionally, public-awareness campaigns and incentives can encourage airlines to adopt greener practices. Altogether, these measures support a policy approach that not only promotes fleet renewal for efficiency, but also ensures that airlines are accountable to global climate goals and societal interests. Our findings highlight the importance of integrating sustainability considerations into both financial and operational aspects of fleet management, aligning industry practice with the imperative of climate change mitigation.

In conclusion, by integrating flexibility, sustainability, and financial prudence into aviation policy frameworks, regulators can help airlines navigate evolving market dynamics while advancing overarching social and environmental objectives. The suite of recommendations outlined above – grounded in the study's analytical results and informed by broader industry trends – provides a roadmap for strengthening airline fleet management through policy. Embracing these insights in a coordinated manner will foster a resilient aviation sector capable of balancing profitability with long-term societal benefits. Ultimately, this research not only offers a decision-support tool for airlines but also serves as a call for policymakers to align industry practices with the public interest, ensuring that fleet management decisions contribute positively to economic stability, environmental stewardship, and the overall sustainability of air transport.

Chapter 7

Conclusions

In this thesis, the issue of fleet management has been studied, including decisions related to purchasing aircraft, leasing aircraft, converting passenger aircraft, selling aircraft, and retiring aircraft. A mixed-integer programming model has been developed for this purpose. Both passenger and cargo demand for the airline have been considered, providing managerial insights into fleet management for both passenger aircraft and freighters. Two options for dealing with aging aircraft have been incorporated: selling or converting them into freighters. Numerical experiments have been conducted to derive insights into the airline's fleet management problem.

The main findings in our study show that operating leases offer airlines flexibility in acquiring aircraft, while purchasing and capital leases boost long-term profitability but increase debt risk. P2F helps reduce debt risk and meets rising cargo demands, though it may not fully address long-term needs and can also impose additional environmental cost. These results highlight the need for strategic fleet management to balance flexibility, profitability, and risk.

While our model provides a comprehensive framework for optimizing fleet management for a single airline under uncertainty, it assumes fully reliable operations and perfect contract fulfillment, abstracting from detailed interactions between multiple airlines and potential operational disruptions. These assumptions facilitate tractable optimization and scenario-based analysis but may limit applicability to complex, dynamic real-world settings. Also, given the critical role of uncertainty in airline strategic planning, as highlighted by de Wit (2022), we recommend that future researchers explore the impact of black-swan events using sophisticated optimization models, such as the online learning methods proposed in Jin (2024). These approaches can mitigate the black-swan effects, such as pandemics or abrupt regulatory changes, on long-term airline planning. Several avenues exist for future research to enhance the model's comprehensiveness and practical relevance. First, integrating network and scheduling optimization could improve the model's ability to address real-world complexities. Additionally, exploring the impacts of strategic alliances and market collaboration on cargo fleet utilization, as well as enhanced demand forecasting through collaborative data-sharing platforms, could provide valuable insights into optimizing fleet decisions under uncertainty. Moreover, the current model does not explicitly incorporate fixed asset values or debt ratios, despite their critical roles in fleet management. For instance, Rosskopf et al. (2014) incorporated fixed asset values into a multi-objective linear programming model to measure an airline's pursuit of maximum wealth, while C.-M. Feng and Wang (2000) argued that debt ratio serves as an indicator of short-term liquidity, and omitting it may lead to biased assessments. Analyzing these financial factors could enrich the literature on airline fleet management. Furthermore, extending the model to consider emerging aircraft technologies, such as hydrogen-powered or electric aircraft, is a promising direction, particularly as reliable cost and performance data become available. Although Justin et al. (2022) and Kinene and Birolini (2024) used integer optimization models to evaluate electric aircraft for regional air mobility, their focus was on small-scale or experimental aircraft. Commercially viable electric aircraft face challenges like limited range, battery technology, and insufficient charging infrastructure, as noted by Klingenberg and Hujer (2024). Finally, given the competitive and cooperative nature of the aviation market, future research could explore fleet management in the context of multiple interacting airlines, building on insights from Wang (2015) and Zheng et al. (2024) to optimize fleet strategies under dynamic market conditions.

Chapter 8

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Chapter 9

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