SMOOTHED DYNAMIC DECISION-MAKING AND NETWORK DESIGN FOR AIRCRAFT ENGINE LOGISTICS

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Smoothed Dynamic Decision-Making and Network Design for Aircraft Engine Logistics

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Certificate of Originality

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Abstract

Aircraft Engine Logistics (AEL) refers to a specific logistics process for aircraft engines that covers all the activities related to the supply, transport, storage, and maintenance of aircraft engines. Efficient AEL is essential in aviation industry as it could ensure the availability and reliability of aircraft engines, thus improve the safety and decrease the delays of flights. In practices, to fulfill the extreme and special requirements in the storage and transportation processes of aircraft engines, airlines have to invest many special physical and human resources to maintain an effective AEL. Meanwhile, due to the uncertainties of engine replacement demands and maintenance time, airlines have to reserve large spaces for engine storage, as well as adjusting its engine scheduling plans accordingly, which greatly increase its operational cost. Thus, reducing the cost of AEL to cope with the increasing competitive aviation industry becomes an important issue for many airlines.

Motivated by real-life cases and focus on the scheduling of engines, this work proposes a new dynamic scheduling approach for aircraft engines and investigate the network design of AEL to decrease its operational costs while improving its efficiency. Specifically, this work systematically examines the decisions of engine scheduling over AEL and develops an integrated engine scheduling model. Then a new dynamic scheduling method that integrates Rolling-Horizon and Event-Driven strategies is developed to deal with both emergency and regular engine replacement and maintenance demands. Besides, this work innovatively proposes smoothed dynamic scheduling of aircraft engines, which considers the switching cost of changing scheduling plans in adjacent decision phases. This enables airlines to balance the waste of setup efforts made for original plan and the potential savings on plan adjustment for changed demands. Furthermore, this work investigates the effect of setting up off-site warehouses in AEL network on the performance of engine scheduling in terms of cost savings.

Extensive experiments based on real-life cases in Hong Kong have been conducted to verify the performance of the proposed method. From the results, it is found that incorporating rolling-horizon and event-driven method is effective in coping with the uncertainties in aircraft engine scheduling, and could well handle the emergency demands. Besides, smoothed decisions can benefit the companies a lot with low engine demand level, not only on avoiding effort wastes and complains, but also could reduce operation cost. Moreover, off-site warehouse is discussed and found effective in saving the cost of AEL and improving the ability to cope with disturbances only with low engine demand.

Keywords: Aircraft Engine Logistics, Dynamic Decision-Making, Smoothed decisions, Switching Cost, Off-site Warehouse, Network Design

Publications

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Wenzhao Dong, Xuan Qiu, & Gangyan Xu*. (2023). Scheduled Transport Service Design for Cross-border Logistics in Airport Cluster. *The 30th International Conference on Transdisciplinary Engineering: Leveraging Transdisciplinary Engineering in a Changing and Connected World, Hua Hin Cha Am, Thailand, July 11-14, 2023.*

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Engine is the heart of an aircraft that provides power of flight, determines its performance, and ensures safe and reliable flight operations (Alomari et al., 2023). It was reported that aircraft engine takes up around 30% of the total manufacturing cost and 40% of the total maintenance cost (Batalha, 2012). Thus, many attentions have been attracted from industries and academia on reducing the operation costs and improving the performance, reliability, and availability of engines (H. Zhou et al., 2022, 2023).

To achieve these goals and support operations, efficient Aircraft Engine Logistics (AEL) is crucial. AEL encompasses the specific logistics processes of aircraft engines, including all the activities related to their replacement, transport, storage, and Maintenance, Repair, and Overhaul (MRO). Through effective coordination with the maintenance activities of aircraft engines, it contributes to reduce downtime and flight delays, and minimize costs (Ma et al., 2022; Ren et al., 2024). Besides, timely and efficient engine delivery can help improve customer satisfaction and the competitive advantage of airlines in the market. Therefore, many efforts have been made by airlines to further improve the efficiency of AEL, such as building more engine shops in different cities, keeping sufficient number of engines, and developing large engine warehouse near hub airports (Kraft & Kuntzagk, 2017).

While these measures have some effectiveness, our field studies reveal that many airlines continue to face high costs and inefficiencies in managing uncertainties within AEL. Maintaining an excess inventory of engines to meet demand can tie up substantial capital, as aircraft engines are extremely expensive. Unlike traditional freight logistics, the holding and transportation costs for aircraft engines are exceptionally high due to stringent safety regulations and specific requirements for storage environments and transport vehicles. According to our investigations in Hong Kong, the monthly holding cost of one ‘hot’ engine (one that is ready for use) is around USD $4,500 and its transportation cost is over USD $9 per kilometer. Additionally, the inherent uncertainties in engine replacement demands pose significant challenges to fixed scheduling plans, leading to substantial additional costs, such as costly downtime of Aircraft On Ground (AOG), and severe flight delays when encountering emergencies. Therefore, there is a pressing need for effective dynamic decision-making methods and network design that are adapted to this scenario to enhance the operational efficiency and cost-effectiveness of the AEL system.

Recognizing that engines are a type of repairable spare part, there are many works on aircraft spare parts logistics (Cakmak & Guney, 2023; Cardeal et al., 2023), including inventory management (Kenzhevayeva et al., 2021) and supply chain coordination (Gallego-García et al., 2021). However, engine logistics is largely different from other spare parts. Engines require specially designed storage facilities, maintenance equipment, and transport vehicles, along with stricter process requirements, leading to separate management and decentralized decision-making within airlines. Currently, limited research has been conducted on AEL, and several challenges and questions are remain to be addressed.

Firstly, the demand for engine maintenance and replacement is dynamic and uncertain. While scheduled maintenance follows a predictable timeline and frequency, unscheduled maintenance can occur unexpectedly due to unforeseen events. This requires airlines to be flexible and responsive to meet these demands, thereby minimizing aircraft downtime.

Secondly, meeting emergency engine maintenance and replacement demands may necessitate rescheduling. While adjusting schedules can potentially reduce overall operational costs, it may also lead to inefficiencies due to the significant setup efforts involved in aircraft engine transportation and storage. Additionally, rescheduling requires extra effort to coordinate among various stakeholders in the logistics process. The trade-off between switching costs and operational cost savings still requires further exploration.

Thirdly, the AEL system continues to experience high logistics costs, which imposes cost pressure for managers during decision-making, even with optimization. Therefore, it is worth discussing whether an off-site warehouse could be beneficial from the perspective of network design. In many logistics systems, off-site warehouse has been widely adopted (Ding & Kaminsky, 2020; N. Li & Wang, 2023; Van der Heide et al., 2018) and proven effective in increasing operation efficiency, reducing costs, and enhancing resilience to disruptions. However, the demand volume in AEL is relatively sparse, and location requirements, such as proximity to major airports, are unique. Besides, an off-site warehouse outside airports may incur additional high-cost transshipment of engines. Further investigation is needed to assess the performance of off-site warehouses in AEL.

1.2 Objectives

Considering the aforementioned challenges and questions, this work proposes a smoothed dynamic decision-making method for aircraft engines and optimizes the network design of AEL to enhance operational efficiency and reduce costs. The specific objectives of this work are as follows:

- To understand the operational processes of AEL and identify current issues for further improvement with detailed analysis.
- To trade off between the plan switching cost and potential cost savings by developing a smoothed dynamic scheduling method for aircraft engines with regular and emergency demands.
- To optimize the AEL network with proposed strategy for effective implementation of a new off-site warehouse.

1.3 Research Content and Methodologies

This thesis addresses the significant operational problems in AEL, identified through comprehensive investigations with airline companies. To enhance efficiency and reduce costs, airlines are focusing on two main strategies. First, they aim to optimize engine scheduling within the existing engine logistics network to improve resource allocation and utilization, thereby achieving greater cost-effectiveness. Additionally, there is potential for further improvements through strategic network optimization, such as introducing an off-site warehouse to enhance overall efficiency. To support these efforts, the research is organized into two main components, as illustrated in Figure 1.1. In the following of this section, the detailed contents in these works will be explained.

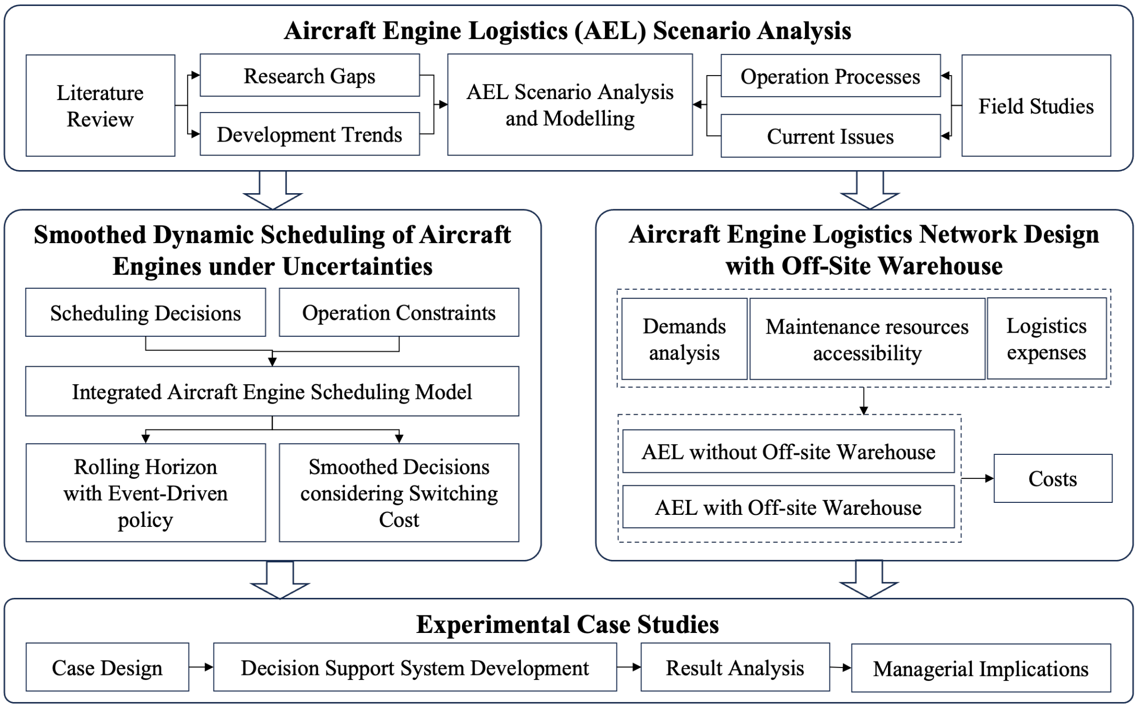

Figure 1.1: Research Framework

The first work involves AEL scenario analysis, aiming to provide insights into the real-world context and gain a comprehensive understanding of the specific constraints and limitations of the problem. This includes examining current operational processes, maintenance and inventory capacities, and identifying major problems and concerns. By thoroughly analyzing AEL operations, these considerations can be incorporated into problem formulation, facilitating the development of practical and feasible solutions tailored to the specific requirements and objectives. Additionally, cost analysis, which involves identifying cost drivers and inefficiencies within AEL operations, can effectively contribute to achieving the model's objectives by providing valuable insights that evaluate trade-offs and support decision-making processes.

The second work focuses on the smoothed dynamic scheduling of aircraft engines. The removal of engines for MRO in airport-adjacent workshops as well as shop visits are considered. Through analyzing the decisions involved and various constraints, an Integer Linear Programming (ILP) model was developed to integrate and coordinate the decisions across different stages. Despite adjusting the plans for improved operational efficiency and cost savings by solving the model, the changes of plans should also be minimized to avoid wasting efforts on previous plans, ensuring decisions are smoothed over different periods. Furthermore, to effectively address both regular and emergency demands, rolling-horizon and event-driven strategies were integrated.

The third work focuses on the AEL network design, specifically the decision of whether to introduce off-site warehouses for temporary engine storage. The complex interactions between transportation and holding costs, along with the intricate setup processes for engine storage and transportation, make it unclear whether and how an airline can benefit from using an off-site warehouse.

Experimental case studies have been conducted for both the second and third works to derive some managerial insights in practice.

1.4 Thesis Outline

According to the research framework discussed above, the remainder of this thesis is organized as follows. Chapter 2 presents a comprehensive literature review encompassing the aircraft maintenance support, dynamic decision making, and logistics network design. The chapter aims to summarize the existing research findings and establish the theoretical foundation for this research. Chapter 3 analyses the operation of AEL. Chapter 4 proposes a smoothed dynamic scheduling method for aircraft engines. Chapter 5 introduces off-site warehouse into AEL network and investigates its performance. Chapter 6 concludes this work and present the future research directions.

Chapter 2

Literature Review

The relevant works can be grouped into three parts: aircraft maintenance support, dynamic scheduling in logistics system, and logistics network design.

2.1 Aircraft Maintenance Support

AEL plays a crucial role in satisfying the demands of engine maintenance and replacement. By ensuring efficient and reliable logistics support, MRO tasks can be executed effectively, leading to reduced flight delays and cancellations (Dinis et al., 2019). This, in turn, enhances customer satisfaction and boosts competitiveness in the aviation market (Gu et al., 2015). Current research on aircraft maintenance support primarily focuses on two key areas: the coordination of maintenance activities with flight schedules and the optimization of spare parts logistics.

2.1.1 Aircraft Maintenance Routing Problem

Considered as a critical component of decision-making processes in support of support aircraft maintenance, the Aircraft Maintenance Routing Problem (AMRP) has been widely studied. It focuses on the scheduling and routing of aircraft to ensure timely maintenance while minimizing disruptions to flight schedules (Liang et al., 2011; Y. Qin et al., 2024). The maintenance resource availability (Eltoukhy et al., 2018; Sarac et al., 2006) and airport capacity (Başdere & Bilge, 2014; Liang et al., 2018) are typically considered. In addition, factors such as flying hours and the number of take-offs, which are linked to the aircraft's initial conditions, also represent major maintenance constraints (Ruan et al., 2021).

To effectively integrate the AMRP into practical applications, many research have extended it by incorporating other operational problems, providing valuable insights into aircraft maintenance decisions. As two of the most critical optimization problems in airline operations, the AMRP and the fleet assignment problem, which assigns aircraft fleets to flight legs, have been jointly addressed to mitigate the risk of maintenance-related delays Liang and Chaovalitwongse (2013). Similarly, the tail assignment problem, which assigns specific individual aircraft to flight legs, has also been combined with AMRP Liang et al. (2015). Besides, to make the most of resources, fleet sizing problem, which aims to determine the minimum required fleet size, has also been integrated with AMRP (Saltzman & Stern, 2022). Furthermore, to minimize disruptions to maintenance schedules and enhance overall airline efficiency, other operational problems that were traditionally addressed sequentially after the AMRP are now being planned in synchronization. These problems include, but are not limited to, crew scheduling (Díaz-Ramírez et al., 2014), crew pairing problems (Ahmed et al., 2018; Parmentier & Meunier, 2020), and the maintenance staffing problem (Yan et al., 2004).

To solve these problems, many works have focused on various optimization and solution methods, including exact optimal solution methods (Başdere & Bilge, 2014), heuristic methods (Cui et al., 2019), and reinforcement learning (Ruan et al., 2021). Specifically, two-stage column generation approach was proposed to efficiently solve large-scale weekly AMRP and proved the optimality of the result (Liang et al., 2015). To address practical problems more effectively and efficiently, researchers have increasingly turned to heuristic methods to streamline decision-making processes. Notable examples in solving the AMRP include the large-scale neighborhood search algorithm (Al-Thani et al., 2016) and the variable neighborhood search algorithm (Cui et al., 2019), which have been employed to explore feasible solutions in a computationally efficient manner. Due to the dynamic nature of the aviation industry, reinforcement learning (RL) offers a more flexible and adaptive framework. In particular, the Q-learning algorithm has been proposed to optimize long-term AMRP (Y. Hu et al., 2021). Additionally, to further protect the maintenance operation and flight schedules against disruptions, robustness framework and optimization methods have also been applied to support aircraft maintenance (Eltoukhy et al., 2019; Maher et al., 2014).

However, current research on decision-making in aircraft maintenance support often fails to adequately address the comprehensive integration of maintenance planning and the associated logistics requirements. Integrating these elements and coordinating various stakeholders in AEL network to ensure the timely availability of essential maintenance resources are crucial for enhancing the overall efficiency and effectiveness of maintenance operations in practical applications.

2.1.2 Spare Parts Logistics

Aircraft spare parts are components used to replace worn-out, damaged, or malfunctioning parts of an aircraft (Q. Hu et al., 2018). They are essential for aircraft MRO and play a critical role in ensuring the safety and airworthiness of aircraft (Cardeal et al., 2023). Efficient logistics and management of spare parts are crucial for reducing MRO costs and enhancing operational efficiency, although such processes are highly complex. Firstly, the variety of spare parts required for aircraft maintenance is vast, numbering in the tens of thousands. Secondly, these parts support both scheduled maintenance tasks and frequent ad-hoc activities leading to potential shortages or overstocking (Kinnison & Siddiqui, 2013). Thirdly, the irregular demand for certain parts, particularly high-value and user-specific components, adds to the complexity of their management (Huiskonen, 2001). Additionally, various participants in aviation MRO activities need collaboration, further complicating logistics (Kilpi et al., 2009). Consequently, airlines frequently maintain large inventories to mitigate the risk of spare parts shortages, which presents significant challenges and costs in inventory management.

Current research on aircraft spare parts logistics (Topan et al., 2020) contributes to enhancing the timely and efficient supply of maintenance resources in a cost-effective manner, with a primary focus on spare parts inventory management and supply chain coordination.

In practices, coping with abnormal and “intermittent” MRO demands often requires maintaining a large stock of spare parts, as any shortages can lead to costly flight cancellations and delays (Singh & Ganguly, 2022). Although irregular demand patterns have been addressed from a systemic perspective (Costantino et al., 2018), accurate demand forecasting is still crucial for effective spare parts inventory management and has driven some research (Hasni et al., 2019). Besides, to satisfy demands and control spare parts inventory, various ordering and scheduling policies for spare parts have been studied (van Jaarsveld et al., 2015; Zhu et al., 2022). The order quantity of aircraft spare parts has been optimized using the Order-Up-To and min-max inventory policies (Kenzhevayeva et al., 2021; Vincent et al., 2022). Due to the complexity introduced by the variety of spare parts, grouping strategies for items with similar stocking policies have been explored (Sheikh-Zadeh et al., 2020). Additionally, uncertainty in spare parts management has been tackled using stochastic programming methods (Y. Qin et al., 2020) and dynamic base-stock policies (X. Qin et al., 2021). To facilitate informed decision-making on spare parts inventory, significant efforts have been made to integrate technology that enhances the traceability and visibility of spare parts. For instance, RFID technology is employed to monitor spare parts and support maintenance activities (E. W. Ngai et al., 2014; E. Ngai et al., 2007). Additionally, a Digital Twin-based intralogistics system has been developed and implemented in a renowned aircraft maintenance company (Q. Chen et al., 2023). Furthermore, Ho et al. (2021) proposed a blockchain-based system that provides a management platform for the accurate recording of spare parts, contributing to the establishment of a digital twin of aviation as part of the Industry 4.0 framework for the future.

While the aforementioned management methods have been effective to some extent, the high volume of different spare parts involved still results in high inventory costs (Regattieri et al., 2005). To alleviate this inventory burden on airlines, strategies such as spare parts pooling (R. Wang et al., 2021) and the development of distribution networks (Gallego-García et al., 2021) have been proposed to enhance coordination within the spare parts supply chain.

However, the unique characteristics of aircraft engines, such as their size, cost, criticality, and regulatory requirements, make their logistics significantly more complex than those of spare parts. Efforts on supporting the aircraft engine maintenance are still needed to improve the efficiency of integrated AEL.

2.2 Dynamic Scheduling in Logistics System

To cope with the dynamics and uncertainties, as well as the incomplete information, dynamic scheduling has been widely studied in many logistics systems, for example, e-commerce logistics (Barenji et al., 2019), food delivery (Zheng et al., 2022), and cold chain logistics (Wu et al., 2022).

In general, the dynamic scheduling problem can be developed as Markov Decision Process (MDP), and solved using dynamic programming (Kleywegt et al., 2004) or reinforcement learning method (Gui et al., 2024; Kang et al., 2019). Meanwhile, there are also many researchers modeled the dynamic scheduling problem as a static scheduling model, and then adopts rolling-horizon like frameworks, or event driven methods to solve it (Ortega et al., 2024). Besides, some works take predicted future status into consideration to improve the quality of static models to dynamic problems (Cai et al., 2023) and some other research incorporate incomplete future information and refine decisions over time using the rolling horizon approach.

However, to adapt the plans as new information emerges, adjustments may be made to the existing schedule, making rescheduling inevitable. Some works trade off between disruption of the original jobs and satisfying new jobs to find Pareto-optimal schedule (R. Chen et al., 2024) and some analyze the impact of recovery operations on the original plan of aircraft usage (Wen et al., 2022). Switching cost has seen considerable interest in electric power system to manage the electricity consumption (Mookherjee et al., 2008; Tanaka, 2006) and has been considered in the trade-off between turning off servers in data centers (Gandhi et al., 2010; Lin, Liu, et al., 2012; Lin, Wierman, Andrew, & Thereska, 2012; Lu et al., 2012). With optimization decision making, the switching cost has also been studied in online convex optimization (N. Chen et al., 2016, 2018; Y. Li et al., 2020; Zhao et al., 2020), smoothed online convex optimization (N. Chen et al., 2018; Goel & Wierman, 2019; Lin, Wierman, Roytman, et al., 2012; G. Shi et al., 2020), and robust optimization over time (Huang et al., 2017; Jin et al., 2013; Yazdani et al., 2018).

While previous studies have advanced our understanding of dynamic scheduling in logistics, the impact of switching costs on AEL is overlooked, particularly where high setup costs are involved. Additionally, there is a lack of exploration into methods that are easily adoptable for practical application in the aircraft maintenance industry to effectively address both regular and emergency demands.

2.3 Logistics Network Design

Warehouses are crucial components of a logistics network, strategically located to serve as hubs that connect suppliers, manufacturers, and customers (Gu et al., 2007). They facilitate seamless integration across the supply chain and enhance the overall efficiency of the logistics network. Many works have been conducted focusing on various aspects of warehouse management related to logistics network design, including the warehouse planning (Y. Shi et al., 2018) and location selection (Ozsen et al., 2008).

Some studies in warehouse planning have explored the use of two warehouses mechanism, including one owned warehouse and one rented warehouse, to manage inventory levels and assess their effectiveness (Lee & Hsu, 2009). A key consideration is whether to rent additional warehouses and what order or shipment policies to implement if extra storage is necessary. Y. W. Zhou and Yang (2005) introduced a model involving two separate warehouses (owned warehouse and rented warehouse) to support decision-making in scenarios with inventory-dependent demand rates. Research has also examined scenarios involving deteriorating items with shortages (Yang, 2004), time-dependent demands (Lee & Hsu, 2009), and imperfect quality production to optimize total profit in two-warehouse inventory models (Chung et al., 2009). In this context, off-site warehouses located outside the demand region have been widely adopted in construction systems, particularly in prefabricated construction, to reduce costs (Bataglin et al., 2024; Xu et al., 2018, 2019).

Effective warehouse location selection can lead to cost savings, reduced transportation times, and ultimately enhance the overall competitiveness of supply chains (Ozsen et al., 2008). The study of warehouse location selection dates back to the 1950s (Baumol & Wolfe, 1958), with the introduction of dynamic programming approaches in 1976 to address these challenges (Sweeney & Tatham, 1976). In the early 2000s, heuristics methods, such as tabu search, were developed to improve the efficiency of solving warehouse location problems (Michel & Van Hentenryck, 2004). Recent research has integrated multiple scenarios, including emergency response (Y. Chen et al., 2016; B. C. Wang et al., 2021) and disaster relief (Rath & Gutjahr, 2014; Roh et al., 2015), while also considering uncertainty and risk. Ozsen et al. (2008) explored the interdependence between capacity issues and inventory management at warehouses, aiming to minimize the sum of fixed facility location, transportation, and inventory carrying costs through risk pooling. Additionally, Hamidi et al. (2017) examined the reliability of warehouse networks to prevent intentional disruptions and enhance reliability before any potential attacks.

Based on the existing research related to off-site warehouse and location selection, previous studies have primarily focused on general goods and products rather than specialized items. To the best of our knowledge, there is a lack of specific research on warehouse decision analysis for aircraft engines, which require specialized facilities and must adhere to strict regulations due to their unique characteristics and requirements. These factors present distinct challenges that differ from those encountered in traditional warehousing scenarios.

2.4 Summary

Existing research provides good theoretical foundation that may assist in AEL decision-making. However, the integration of maintenance planning with logistics for aircraft engines remains underdeveloped. The complexities arising from the unique characteristics of aircraft engines are not yet fully addressed, making their logistics more intricate than those of spare parts. Practical decision-making approaches that the industry can readily implement to address both routine and emergency logistics demands, while considering switching costs, particularly in scenarios with significant setup expenses, still need to be developed. Additionally, research on warehouse decision-making has predominantly focused on general products, overlooking the specialized requirements of aircraft engines, which demand unique facilities and strict regulatory compliance. Addressing these gaps is crucial for enhancing the efficiency and effectiveness of AEL.

Chapter 3

Operational Analysis for Aircraft Engine Logistics

3.1 Introduction

Given the critical importance of aircraft engines and the substantial costs associated with AEL, ensuring engine availability and reliability is crucial for airlines. To address these needs, some manufacturers have started to offer specialized services, including monitoring, data analysis, and comprehensive maintenance support, aimed at enhancing operational availability, reliability, and efficiency in engine management. For instance, Rolls-Royce has announced that Cathay Pacific has ordered 60 Trent 7000 engines under a TotalCare service agreement, which will cover their entire engine fleet (Rolls-Royce, 2024a). TotalCare, supported by data from Rolls-Royce's advanced engine health monitoring system, helps maximize engine flying potential and alleviates the burden of engine maintenance by transferring time-on-wing and maintenance cost risks to Rolls-Royce (Rolls-Royce, 2024b). However, to fully leverage the benefits of this service, it is crucial to ensure a timely response to the insights it provides. This necessity creates a need for an efficient AEL system to ensure that engines remain airworthy and available when needed, thereby minimizing downtime and costs (Ren et al., 2024).

Our field studies reveal that many airlines are still suffering from high operation cost in managing AEL. Unlike traditional freight logistics, AEL is managed separately from spare parts logistics due to the unique challenges it presents. The holding and transportation costs for aircraft engines are exceptionally high, driven by stringent safety requirements and the need for specialized storage environments and transport vehicles. According to our investigations in Hong Kong, the holding cost of one hot engine (engine that is ready to use) per month is around USD $4,500 and its transportation cost is over USD $9 per kilometer. Therefore, it is crucial to analyze the operational processes and practical challenges of AEL to enhance its efficiency.

The remainder of this chapter is organized as follows. Section 3.2 illustrates the AEL network. Section 3.3 presents the operation processes. Section 3.4 analyzes the current issues. Section 3.5 summarizes this chapter.

3.2 Aircraft Engine Logistics Network

AEL network refers to the integrated system of facilities, processes, and resources involved in the transportation and storage of aircraft engines throughout their life-cycle. It is crucial for ensuring that engines are efficiently managed and available to satisfy the demands in the aviation industry. Figure 3.1 shows a typical AEL network example. Generally, all nodes are connected by edges, but the edges' services may not necessarily be the same, which have not been fully illustrated in Figure 3.1.

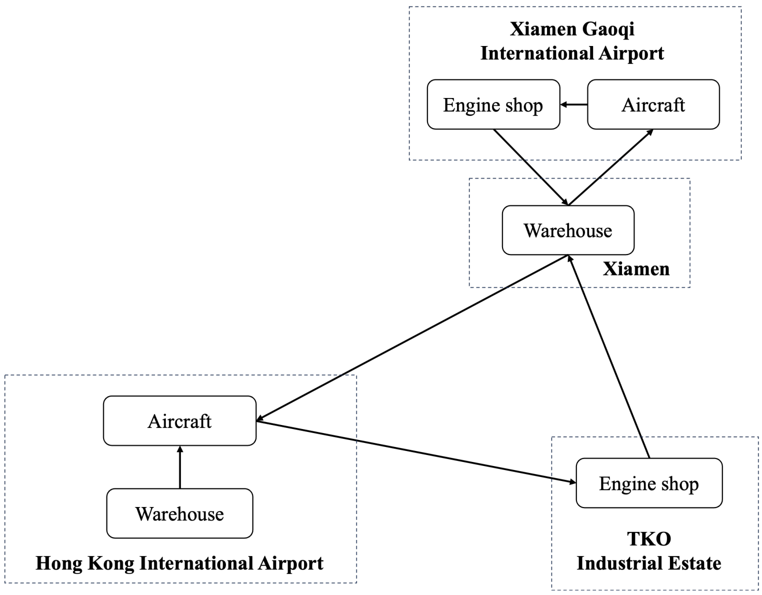

Figure 3.1: Example of AEL Network.

1) The nodes in AEL network:

The nodes include demand nodes (aircraft in airport), storage nodes (warehouse), maintenance nodes (engine shop for engine maintenance activities). In practices, some nodes can be physically located in the same area. For example, at Hong Kong International Airport (HKIA), there are both a demand node and a storage node. This means that demand will occur at HKIA and the engine can be stored in a warehouse located within the airport. Nearby, in the Tseung Kwan O (TKO) industrial estate, there is an engine shop where the engines can be maintained. Xiamen Gaoqi International Airport (XGIA) is also part of this network, featuring a demand node and an engine shop. Unlike Hong Kong, however, Xiamen has a warehouse located outside the airport.

2) The edges for M-Engines:

   The M-Engines (engines to be maintained) will be transported from the demand node to either the warehouse or the engine shop, or from the warehouse to the engine shop. This means that the faulty engines will ultimately arrive at the engine shop for maintenance, after which their status will be updated to 'hot engine'.

3) The edges for H-Engines:

   The H-Engines (hot engines, engines that are ready to use) will be transported from the engine shop to either the demand node for direct use or to the warehouse for storage, or from the warehouse to the demand node. This means that the routes for hot engines will begin at the engine shop and ultimately arrive at the demand node when needed.

Unlike other logistics networks, the AEL network has unique demands, including engine replacements conducted at demand nodes and maintenance performed at specialized engine shops. The transportation and storage activities within this network are designed to effectively facilitate timely maintenance and replacement services. This coordination is crucial for minimizing aircraft downtime, ensuring that they remain operational and compliant with safety standards.

3.3 Operation Processes of Aircraft Engine Logistics

Given the critical importance of safety and the substantial costs of maintenance visits, which can amount to several million dollars, well planning of engine shop visits is essential. The operation of AEL encompasses four key processes: engine replacement, transportation, maintenance, and storage.

3.3.1 Aircraft Engine Replacement

In the aviation industry, ensuring safety is of high priority and importance. Regular engine maintenance and timely upgrades are necessary to ensure efficient and safe aircraft operation, necessitating engine replacement.

According to Federal Aviation Administration (FAA), engine may need to be removed for maintenance due to some common reasons, for example, exceeding the engine or component lifespan, sudden stoppage of engine, sudden reduction in engine speed, metal particles in the oil, spectrometric oil analysis engine inspection program, turbine engine condition monitoring programs, and some engine operational problems. Besides these reasons, the engines undergo complete overhauls two or three times before being taken out of service. According to investigations, the modern narrow-body engines average approximately 12,000 flight cycles before their first overhaul, with subsequent maintenance visits occurring at around 8,000 and 4,000 cycles, respectively. For modern wide-body engines, the average time before the first overhaul is about 20,000 flight hours, with subsequent visits potentially reduced to as low as 5,000 flight hours. In addition to these maintenance needs, the limited lifespan of engine components means that the aircraft typically require around three to four sets of engines over their operational lifetime, depending on how long that lifespan is. This replacement is inevitable, as the engines will not last for the aircraft's entire lifespan. An aircraft's lifespan is measured in flight cycles, which consist of a completed takeoff and landing, regardless of the distance flown. Therefore, the engine replacement is of high demand.

While the processes and procedures for removing and installing an aircraft engine can vary widely depending on the type of aircraft and engine, there are some common tasks and procedures that must be followed to ensure safety. For efficiency, an airworthy engine should be prepared for installation concurrently with the decision to remove the existing engine. When the new or overhauled engine is ready for installation, numerous regulations and procedures must be adhered to, including ground operations, flight tests, and visual inspections. The engine removal and installation involves multiple procedures and numerous checks to ensure safety, which require significant setup time and effort for airlines.

3.3.2 Aircraft Engine Transportation

After engine replacement, the next critical step is the transportation of engine, which requires expertise, specialized equipment, and thorough planning. Engines may need to be transported to the warehouse for storage, to the engine shop for maintenance, or to the airport for replacement. Effective coordination among various procedures and multiple stakeholders is essential to ensure a safe and seamless transportation process.

In current practice, several challenges arise in transporting engines. Firstly, engines are not only massive but also heavy, necessitating specialized equipment such as cranes, special forklifts, and heavy-duty trucks to move and accommodate them. Secondly, aircraft engines consist of thousands of precision metal parts, which are fragile and sensitive to external forces, shock, and vibration. Therefore, protecting them during transportation through secure packaging and careful handling to ensure their safe delivery. Additionally, the high cost of transportation poses a significant challenge for airlines. Transporting aircraft engines is expensive due to their size, weight, and unique requirements, such as customized packaging and specialized equipment, as mentioned above. According to our field study with a leading airline, the engine transportation cost is over USD $9 per kilometer. And any emergency damage to the aircraft engine during transport can lead to substantial maintenance costs. Therefore, engine transportation requires much attention and strict adherence to safety regulations.

3.3.3 Aircraft Engine Maintenance

Aircraft maintenance involves broad types of tasks and duration. In general, it can be classified into transit checks, A-checks, B-checks, C-check, or D-check (Başdere & Bilge, 2014; Ma et al., 2022). It can be time-consuming, for example, Emirates completed a '3C - check' for its first A380 in 2014, which took 55 days. During the check, each of the four engines were also removed, inspected and overhauled (Australian Aaviation, 2014).

Aircraft engine maintenance encompasses tasks that ensure the engine and its systems remain in an airworthy condition while on the wing. It also includes the work required to return the engine to airworthy condition when it is removed from an aircraft. For scheduled maintenance, the maximum duration an engine can remain installed in an aircraft is limited to a fixed period agreed between the engine manufacturer and airworthiness authority, which is complex and may depends on how the engine is used. However, unscheduled maintenance may be required due to unexpected events not typically related to time limits, such as bird ingestion, crashes, heavy landings, or other malfunctions.

Engine maintenance services can vary by type, location, and outsourcing arrangements (Y. Qin et al., 2024). For example, the HAESL workshop in Hong Kong offers maintenance, repair and overhaul (MRO) services, as well as testing for Rolls-Royce Trent 700, 800 and XWB engines, specializing in the repair and overhaul of strategic engine components such as turbine blades and fan blades. In Mainland China, HAECO Engine Services (Xiamen) provides comprehensive services for GE90 engines.

3.3.4 Aircraft Engine Storage

Engine storage is also an important part of AEL, not only for the protection of engines but also for the effective management. There are three types of engine storage: active engine, temporary, and indefinite, distinguished by the engine conditions and storage duration. During the storage for awaiting overhaul or return to service after overhaul, to extend the lifespan of engines, it is essential to take careful measures to protect engines from environmental factors such as moisture, dust, and temperature fluctuations, which can lead to corrosion and other forms of damage.

Furthermore, to ensure that engines are readily available when needed and to minimize downtime for aircraft, the engine storage should facilitates easier access for demands. Having a well-organized storage system enables shorter response times to demand fluctuations, enabling better management of engines to reduce holding costs and improve overall operational efficiency.

However, in practice, high land rental costs can significantly contribute to the overall storage expenses for engines. According to our field study with a leading airline, the monthly storage fees for engines at Hong Kong International Airport (HKIA) are approximately \$40,000 HKD per large engine and \$30,000 HKD per small engine, compared to around \$7,000 HKD in Xiamen.

3.4 Current Issues

Current issues of AEL operation exist in three parts: the uncertainties in AEL, high operation costs, and decentralized decision-making.

3.4.1 Uncertainties in Aircraft Engine Logistics

The uncertainties exist in all the operation processes of AEL. Firstly, the aircraft engine replacement and maintenance demand is of high uncertainty. In addition to scheduled maintenance plan based on flight hours or cycles, any damage caused by incidents and unexpected failures of engine parts may necessitate immediate thorough inspections and maintenance to ensure safety and reliability. And sometimes the components or systems of engines may need to be upgraded. In addition, a sudden failure of one engine may require all engines of the same model to be removed and maintained. Foe example, Cathay Pacific's A350 engine defect happened on Sept 2024, and the fleet-wide inspection of its 48 Airbus A350 aircraft was conducted with the finding that a number of the same engine components were needed to be replaced (CNN, 2024). Also, emergency engine replacement and maintenance demands frequently occur with the increasing of flights.

Secondly, the aircraft engine maintenance time is also of uncertainty. Engines are intricate systems with multiple kinds of maintenance tasks, and the unexpected issues may arise during maintenance, resulting in extended maintenance duration. Besides, the maintenance tasks require the highly cooperation of many maintenance experts, meaning that the skill levels and availability of maintenance personnel can significantly impact the efficiency of the maintenance process. Furthermore, numerous spare parts and tools are essential for these maintenance activities. Given the wide variety of spare parts and tools required, managing their inventory poses significant challenges and the supply chain is usually of high disruption risks. (X. Li et al., 2016). It is important to note that the engine transport time can also be uncertain due to a variety of factors, such as the traffic and weather conditions and specific vehicle availability.

3.4.2 High Costs in Aircraft Engine Logistics Processes

As mentioned in Section 3.3, the transportation and storage of engines are of high costs. The engine transportation requires expertise and specialized equipment, such as cranes, special forklift, and heavy-duty trucks, and customized secure packaging, all of which are essential due to the unique characteristics of the engines and the stringent safety requirements. Additionally, as mentioned above, engine storage has high requirements to protect engines from environmental factors that can lead to corrosion and other forms of damage. Meeting these requirements incurs significant costs, which are likely to be even higher if the engines are stored near the airports. Reducing the costs in operation is of much importance for airlines.

3.4.3 Decentralized Decision-Making in Aircraft Engine Logistics

The operation of AEL involves four key processes: engine replacement, maintenance, transportation and storage. However, our investigation reveals that the decision-making in AEL to satisfy the engine demand has not been effectively integrated in practice. The lack of integration can lead to inefficiency in storage management and reduce the availability of airworthy engines. By coordinating these processes, better information sharing can be achieved through the integration of data on engine demands, maintenance schedules, and storage capacities. This approach can help optimize inventory levels, reduce delays, and enhance overall operational efficiency. Therefore, it is essential to coordinate decision-making across all AEL processes.

3.5 Summary

AEL includes many entities and requires coordination between different processes and stakeholders to ensure the safety and availability of engines, while facing the problems of uncertainty, high cost, and lack of decision integration. The works presented in Chapter 4 and 5 are dedicated to coping with these problems through smoothed dynamic scheduling of engines and logistics network design.

Chapter 4

Smoothed Dynamic Scheduling of Aircraft Engines under Uncertainties

4.1 Introduction

In the daily operations of airlines, efficient scheduling of aircraft engines (including both faulty engines and hot engines) to satisfy the engine replacement and maintenance demand is important for reducing aircraft downtime and flight delays, saving cost, and improving the operation efficiency (Ma et al., 2022). Many efforts have been made by airlines to further support the aircraft engine scheduling, such as contracting with more engine shops for maintenance services in different cities, keeping sufficient number of engines, and developing large engine warehouse near hub airports (Kraft & Kuntzagk, 2017).

Although such measures are effective to some extent, our field studies reveal that many airlines are still suffering from high operation cost and inefficiency in managing AEL to cope with uncertainties. The inherent uncertainties arise in emergency demands greatly challenges the fixed engine scheduling plans, leading to extremely high extra cost and severe flight delays. Thus, it is vital to develop effective dynamic engine scheduling methods for a more efficient and resilient AEL system.

Many works have tried to reduce costs and enhance the efficiency of logistics systems in aviation industry. While aircraft engine is one typical repairable spare part, its logistics is largely different from the others. The specialized logistics requirements of engine set it largely apart from other spare parts. The specially designed storage facilities and transport vehicles required, as well as the stricter requirements on the entire AEL processes, necessitate that the AEL operations be managed separately in airlines. Additionally, the coordination of multiple stakeholders and activities to serve the demand of maintenance and replacement also add pressures for managing the AEL system. Currently, there are still limited works able to address these problems and bridge this gap. Cost-effective and efficient engine scheduling methods are urgently in need, while several challenges still remain.

Firstly, given highly uncertain engine replacement demands, it is a challenge to design an effective dynamic scheduling method that could improve the efficiency of demand satisfaction while decreasing the cost. Meanwhile, the scheduling of aircraft engines in AEL always suffers from long preparation and transportation time, which hinders the effective adoption of event-driven or online decision method. Besides, emergency engine replacement demands, which are difficult to forecast, frequently occur with the increasing of flights, further challenges the scheduling strategies of engines.

Secondly, considering the high setup effort of aircraft engine transportation and storage, how to trade off between the changes of scheduling plans and cost savings? Different from other logistics processes, the rescheduling of engines will induce high sunk costs and require extremely high extra efforts to coordinate various stakeholders, processes, and related resources. These efforts include not only the setup cost and time, but also hidden pressure and complains from stakeholders and operators, especially when facing sharp and frequent changes of plans. However, such efforts are seldom considered in literature and it is still unclear how they will affect the dynamic decisions and their performances.

Taken above problems and challenges into consideration, this chapter proposes a smoothed dynamic scheduling method for aircraft engines. Specifically, the contributions of this work lie in the following three aspects.

- All the decisions in AEL process to support the engine maintenance and replacement demands are coordinated and integrated into a model.
- A smoothed dynamic scheduling method for aircraft engines is developed that trade off between the plan switching cost and potential operation cost savings.
- By integrating rolling-horizon and event-driven strategies, the proposed method could well cope with both regular demands and emergency demands.

The remainder of this chapter is organized as follows. Section 4.2 discusses the workflow of aircraft engine scheduling. Section 4.3 analyzes the decision-making in aircraft engine scheduling. Section 4.4 models the problem and Section 4.5 discusses the proposed smoothed dynamic scheduling method. Experimental case studies are conducted in Section 4.6. Section 4.7 summarizes the work of this chapter.

4.2 Workflow of Aircraft Engine Scheduling

To ensure the safe and efficient operation of aircraft, engines need to be removed from aircraft for maintenance regularly, based on the Landing Take-Off (LTO) cycle and flight hours. Meanwhile, emergency engine maintenance demands appear randomly due to incidents or their unpredictive malfunctions. To support such maintenance activities, airlines need to make effective schedules for engines to be maintained (M-Engines) and hot engines (H-Engines, engines that are ready to use).

According to our investigations to several airlines in Hong Kong, the workflow of aircraft engine scheduling can be depicted in Figure 4.1, which consists of three main steps.

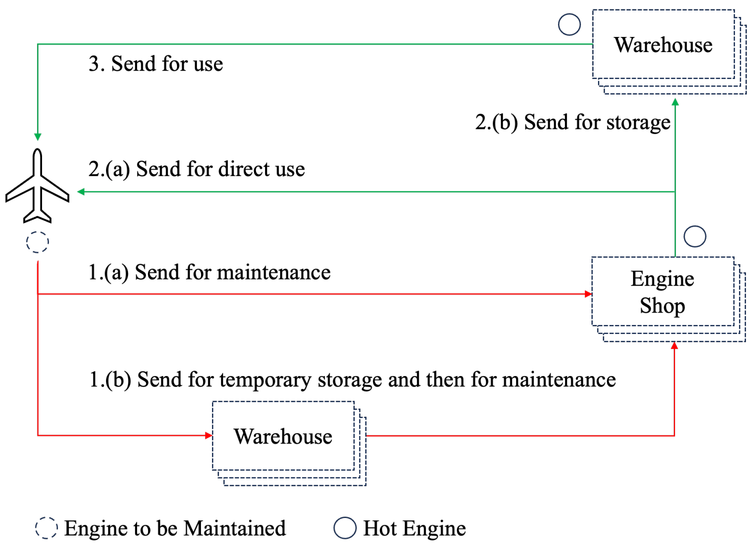

Figure 4.1: Workflow of Aircraft Engine Scheduling.

4.2.1 Dispatch M-Engines

When there is an Engine Replacement and Maintenance (ERM) demand, the airline should decide when and where to send the removed M-Engines. In practices, the airline will check the available maintenance slots in collaborative engine shops, then decides which engine shop to send (*Step 1(a)* in Figure 4.1), with the consideration of engine transportation cost and time, and predictive distribution of future ERM demands. The airline can also send the M-Engines to warehouses for temporary storage before sending for maintenance (*Step 1(b)* in Figure 4.1).

4.2.2 Dispatch H-Engines (from engine shops to warehouses or aircraft)

After the maintenance at engine shops, the M-Engines become H-Engines that are ready to be assembled on an aircraft. The airline should decide where to send these H-Engines for storage or for direct use, considering current unsatisfied demands, engine transportation cost, the availability of storage spaces at different warehouses and the corresponding holding cost, as well as the predictive future ERM demands.

4.2.3 Dispatch H-Engines (from warehouses to aircraft)

At the same time of *Step 1*, the airline should also decide to dispatch the H-Engines to be used for fulfilling the ERM demand. The number of H-Engines needed is as same as the number of M-Engines removed from the aircraft. The decisions mainly considers the transportation cost and time of H-Engines from warehouse to the aircraft and the predictive future ERM demands.

4.3 Decision-Making in Aircraft Engine Scheduling

The aircraft engine scheduling decisions in the above three steps are dependent with one another, jointly determining the flow of M-Engines and H-Engines within the AEL network. However, in practices, these decisions are conducted individually by different departments, hindering cooperative decisions that could improve efficiency and withstand disturbances from demand changes or emergency demands. The decisions in *Step 1* are usually made on a rolling-horizon basis. That is, the airline makes the M-Engine dispatching plans periodically based on available ERM demand information in a given period, and dynamically adjusts the plan according to the reveal of new information. Besides, the demands for H-Engines will be released with predictive deadlines based on the ERM demand. The decisions in *Step*

2 and *Step 3* on dispatching H-Engines are usually conducted in an event-driven mode. It means only when an engine is about to finish maintenance or the deadline for H-Engine is approaching, the schedule plans on H-Engines will be made.

Although integrated scheduling decisions across three steps are promising, the uncertainties and large time-lag between different steps makes it challenging. On one hand, the ERM demands are highly uncertain that are frequently affected by flight plans, environments, incidents, and other unpredictive events. On the other hand, the setup and transportation time cannot be neglected between different steps, thus brings large time-lag between different steps. These lead to asynchrony of decisions in different steps, further impeding integrated decisions made simultaneously.

4.4 Integrated Aircraft Engine Scheduling Model

To improve the performance of aircraft engine scheduling, this work proposes to integrate and coordinate the decisions in different steps, rather than conducted individually. Considering a batch of ERM demands in a given period $\mathcal{T}_0$, the integrated aircraft engine scheduling model is developed in this section, and the notations adopted are given in Table 4.1.

In general, there are two main decisions. One is the scheduling of M-Engines (decisions in *Step 1*), represented by $x_{i,j}^t$, and the other is the scheduling of H-Engines (decisions in *Step 2* and *Step 3*), denoted as $y_{i,j}^t$. The objective of aircraft engine scheduling is to meet all the ERM demands with minimize cost within a pre-defined period $\mathcal{T}$, includes transportation cost and holding cost of engines, and penalty induced by delays. The costs of inter-site logistics are taken into account, as well as the intra-site costs at the airport, since handling engines incurs significant expenses that cannot be overlooked.

The transportation cost of engines can be calculated as:

$$C_t = \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{E}\cup\mathcal{W}} \sum_{i\in\mathcal{A}\cup\mathcal{W}} x_{i,j}^t \cdot c_{i,j} + \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{A}\cup\mathcal{W}} \sum_{i\in\mathcal{E}\cup\mathcal{W}} y_{i,j}^t \cdot c_{i,j} \tag{4.1}$$

The holding cost is dependent on engine transport schedules, and can be calculated as follows:

$$C_h = \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{W}} (q_i^t + m_i^t) \cdot h_i \tag{4.2}$$

Table 4.1: Notations

Indices	
i, j	index of node
t	index of time
Sets	
$\mathcal{A}$	demand node set
$\mathcal{E}$	maintenance node set
$\mathcal{W}$	storage node set
$\mathcal{T}_0$	planning period
$\mathcal{T}$	scheduling period
Parameters	
T_m	maintenance duration for each engine
t_0	planning start time
α	penalty rates for delayed regular ERM demands
β	penalty rates for delayed emergency ERM demands
θ	unit switching cost
h_i	holding cost for engine at node i ($ /unit/day)
$c_{i,j}$	unit transport cost for engines from node i to j
$z_{i,j}$	transport time from node i to node j (day)
d_i^t	regular ERM demands at node i at time t (units)
ed_i^t	emergency ERM demands at node i at time t (units)
K_i	total maintenance capacity of node i (units)
Q_i	total inventory capacity of node i (units)
Decision Variables	
$x_{i,j}^t$	number of M-Engines transported from node i to j at time t (units)($i \neq j$)
$y_{i,j}^t$	number of H-Engines transported from node i to j at time t ($i \neq j$)
Intermediate Variables	
q_i^t	inventory of H-Engines at node i at time t
m_i^t	inventory of M-Engines at node i at time t
u_i^t	delayed regular ERM demands at node i at time t
v_i^t	delayed emergency ERM demands at node i at time t
r_i^t	satisfied regular ERM demands at node i at time t

For delayed fulfillment of ERM demand, a penalty will be incurred, as depicted below:

$$C_{p1} = \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{A}} u_i^t \cdot \alpha \tag{4.3}$$

In practices, the fulfillment of emergency ERM demand usually has higher priority, thus delay will incur higher penalty:

$$C_{p2} = \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{A}} v_i^t \cdot \beta \tag{4.4}$$

With the above analysis, the integrated model of aircraft engine scheduling can be given as follows:

$$\textbf{minimize } C = C_t + C_h + C_{p1} + C_{p2} \tag{4.5}$$

subject to:

$$d_i^t + ed_i^t = \sum_{j \in \mathcal{E} \cup \mathcal{W}} x_{i,j}^t, i \in \mathcal{A}, t \in \mathcal{T} \tag{4.6}$$

$$u_i^{t-1} + d_i^t = r_i^t + u_i^t, i \in \mathcal{A}, t \in \mathcal{T} \tag{4.7}$$

$$v_i^{t-1} + ed_i^t = \sum_{j \in \mathcal{E} \cup \mathcal{W}} y_{j,i}^{t-z_{j,i}} - r_i^t + v_i^t, i \in \mathcal{A}, t \in \mathcal{T} \tag{4.8}$$

$$r_i^t \leq \sum_{j \in \mathcal{E} \cup \mathcal{W}} y^{t-z_{j,i}}, i \in \mathcal{A}, t \in \mathcal{T} \tag{4.9}$$

$$q_i^{t-1} + \sum_{j \in \mathcal{E}} y_{j,i}^{t-z_{j,i}} = q_i^t + \sum_{j \in \mathcal{A}} y_{i,j}^t, i \in \mathcal{W}, t \in \mathcal{T} \tag{4.10}$$

$$m_i^{t-1} + \sum_{j \in \mathcal{A}} x_{j,i}^{t-z_{j,i}} = m_i^t + \sum_{j \in \mathcal{E}} x_{i,j}^t, i \in \mathcal{W}, t \in \mathcal{T} \tag{4.11}$$

$$m_i^{t-1} + \sum_{j \in \mathcal{A} \cup \mathcal{W}} x_{j,i}^{t-z_{j,i}} = m_i^t + \sum_{j \in \mathcal{A} \cup \mathcal{W}} y_{i,j}^t, i \in \mathcal{E}, t \in \mathcal{T} \tag{4.12}$$

$$\sum_{j \in \mathcal{A} \cup \mathcal{W}} x_{j,i}^{t-z_{j,i}-T_m} = \sum_{j \in \mathcal{A} \cup \mathcal{W}} y_{i,j}^t, i \in \mathcal{E}, t \in \mathcal{T} \tag{4.13}$$

$$d_i^t = 0, i \in \mathcal{A}, t \in (\mathcal{T} - \mathcal{T}_0) \tag{4.14}$$

$$ed_i^t = 0, i \in \mathcal{A}, t \in (\mathcal{T} - \mathcal{T}_0) \tag{4.15}$$

$$m_i^t \leq K_i^t, i \in \mathcal{E}, t \in \mathcal{T} \tag{4.16}$$

$$q_i^t + m_i^t \le Q_i, i \in \mathcal{W}, t \in \mathcal{T} \tag{4.17}$$

$$x_{i,j}^t, y_{i,j}^t, q_i^t, m_i^t, u_i^t, v_i^t, r_i^t \in \mathcal{N} \tag{4.18}$$

Here, Equation (4.5) is the objective function that minimizes the total cost of transportation, storage, and penalty.

Constraints (4.6) - (4.13) are flow balancing constraints for both M-Engines and H-Engines. Specifically, constraint (4.6) means the number of M-Engines removed from aircraft should equal to the number of H-Engine needed. Constraints (4.7) and (4.8) represents the status of demand fulfillment. $(u_i^{t-1} + d_i^t)$ denotes the total regular ERM demands, and $(v_i^{t-1} + ed_i^t)$ denotes the total emergency ERM demands. Constraints (4.10) and (4.11) are the flow balancing constraints for M-Engines and H-Engines at warehouses respectively. Constraints (4.12) and (4.13) represents the status transfer of engines, from M-Engines to H-Engines.

Constraint (4.9) limits the number of H-Engines for fulfilling regular ERM demands should be less than available H-Engines. Constraint (4.14) and (4.15) assume the ERM demand beyond $\mathcal{T}_0$ is set as 0, since in the current stage, the information of future ERM demands is not available. Constraint (4.16) is the maintenance capacity constraint at engine shops and Constraint (4.17) is the inventory capacity constraint. Constraint (4.18) means all decisions variables are nonnegative integers.

4.5 Smoothed Dynamic Aircraft Engine Scheduling

Based on the static model presented in Section 4.4, this section proposes an effective dynamic scheduling method. Then, the plan switching cost are analyzed, upon which the smoothed dynamic decision method is developed.

4.5.1 Rolling-Horizon and Event-Driven Dynamic Scheduling

In aircraft engine scheduling processes, there are two typical types of ERM demands. One is regular ERM demand that is revealed periodically according to flight plans. The other is emergency ERM demand that occurs suddenly due to detected malfunctions of engines, incidents, and accidents. To cope with these two types of ERM demands and coordinate the decisions in different steps, this work proposes a Rolling-Horizon and Event-driven (RH-E) method for dynamic aircraft engine scheduling in AEL.

The general idea of proposed RH-E method is illustrated in Figure 4.2. Specifically, the scheduling of engines for regular ERM demands are conducted in rolling-horizon basis while the event-driven strategy is adopted for emergency ERM demands to realize efficient responses.

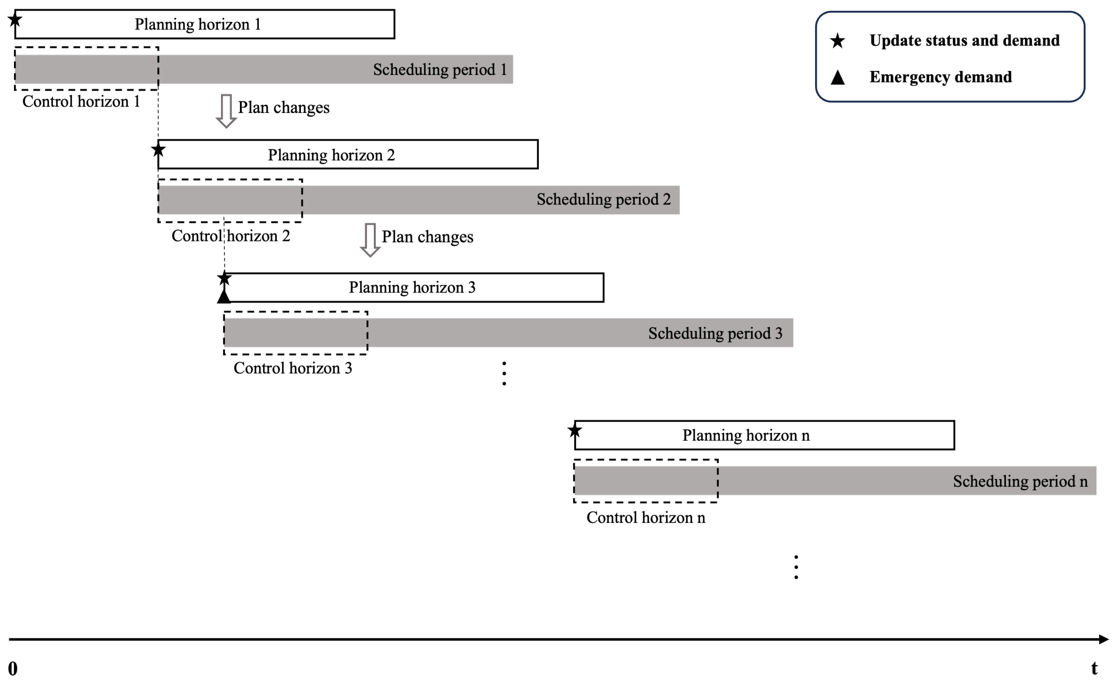

Figure 4.2: Rolling-Horizon and Event-driven (RH-E) Strategy.

For every decision point, the airline will consider all available regular ERM demands in the planning horizon ($\mathcal{T}_0$), and then make optimal decisions based on the model presented in Section 4.4. After the execution of scheduling plan for a given period ($\mathcal{T}_c$), i.e., control horizon, new information will be collected for ERM demands in the upcoming $\mathcal{T}_0$ period, and a new round of decisions can be made.

During the execution of scheduling plan for regular ERM demands, once there is an emergency ERM demand, it will trigger the rescheduling process, i.e., the event-driven decisions. Specifically, in this work, the rescheduling process not only considers the emergency ERM demand in priority, but also all the available regular demands in the next $\mathcal{T}_0$ period to make integrated decisions. That is, a new round of rolling-horizon decision process starts.

The proposed RH-E method distinguishes itself from existing rolling-horizon practices by not adhering to strictly periodic decision-making based on a fixed control horizon. Instead, decision points are dynamically adjusted in response to emergency Engine Resource Management (ERM) demands. This approach triggers new planning cycles either when emergency events occur or at the end of a control horizon. It offers greater flexibility in adapting to demand changes and can better coordinate resources by considering both regular and emergency demands. Additionally, because it aligns with current practices, the method is easy to adopt in real-world scenarios.

4.5.2 Smoothed Decisions Considering Switching Cost

In the proposed RH-E method, the scheduling plans will be adjusted at each decision point, which leads to the changes of engine transport and storage plans. As mentioned in previous sections, the setup cost for engine transport and storage is very high, and any changes will lead to the waste of preparation efforts. Meanwhile, according to our investigations, the operators are resistant to make changes, thus frequent changes of plans will also lead to complains from them. Therefore, besides adjusting the plans for potential operation efficiency improvement and cost savings in aircraft engine scheduling, the changes of plans should be minimized to avoid the waste of efforts on previous plans and complains raised, which means the decisions should be smoothed across different periods.

In this work, *switching cost* is introduced to represent all the cost associated with the changes of plans, including the efforts wasted and complains raised. *Switching cost* is dependent on the extent of changes and the lead-time to changes. It is obvious that larger changes will have higher *switching cost*. The lead-time to changes is defined as from the plan change time to the execution time of original plan. Relatively more efforts should be made to response to changes if the lead-time is shorter, thus would induce higher *switching cost*. If the lead-time is long, the transport or storage setup process may not start yet and operators may have longer time to prepare, thus has lower *switching cost*. With the above analysis, the *switching cost* can be calculated as follows:

$$C_{sc} = \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{E} \cup \mathcal{W}} \sum_{i \in \mathcal{A} \cup \mathcal{W}} \frac{\theta \cdot (|\Delta x_{i,j}^t| + |\Delta y_{j,i}^t|)}{(t - t_0)} \tag{4.19}$$

To realize smoothed dynamic decision-making, the decisions made at each decision point in the RH-E method should balance between the potential cost savings and the *switching* *cost*. In this work, at each decision point, the objective of engine scheduling should consider the impact of *switching cost*, thus Equation (4.5) is revised as follows:

$$\textbf{minimize } C = C_t + C_h + C_{p1} + C_{p2} + C_{sc} \tag{4.20}$$

Through incorporating the *switching cost* in the objective function, the adjustment of engine scheduling plans at different decision points will be kept in a reasonable range, which makes the schedules smoothed along with time.

4.6 Experimental Case Study

In this section, several experimental case studies are conducted to verify the performance of the proposed method. Then, several managerial implications are discussed.

4.6.1 Experiment Settings

Scenario Description. Three experimental cases are developed based on the scenario in Hong Kong, as depicted in Figure 4.3, Figure 4.4 and Figure 4.5. Case 1 (Figure 4.3) is the basic scenario that only contains one demand node, one warehouse, and one engine shop. Here, the demand node and warehouse are located in HKIA while the engine shop is located in TKO industrial estate of Hong Kong, which is around 50 km from HKIA. Compared with Case 1, Case 2 (Figure 4.4) includes Xiamen Gaoqi International Airport (XGIA), which has one demand node, and one engine shop, and also includes one warehouse in Xiamen. In addition, Chengdu Tianfu International Airport (CTIA) is included in Case 3 (Figure 4.5), which serve as one demand node and one warehouse.

Parameter setting. In the three cases, the holding costs per engine per day in Hong Kong, Xiamen, and Chengdu are set as HKD \$1421, \$228, and \$200 respectively. he transportation cost for one engine per kilometer is HKD \$71. Without loss of generality, the planning horizon in all experiments are set as 30 days, maintenance time for each engine is 7 days, and the total studied period is 1 year (365 days). Align with industrial practices, the control horizon is set in the range from 7 to 21 days.

Demand setting. For Case 1, we randomly generated a set of aircraft engine replacement and maintenance demands at HKIA, encompassing high, medium and low demand levels.

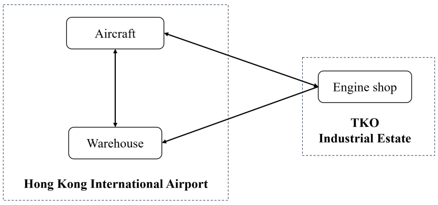

Figure 4.3: AEL of Case 1.

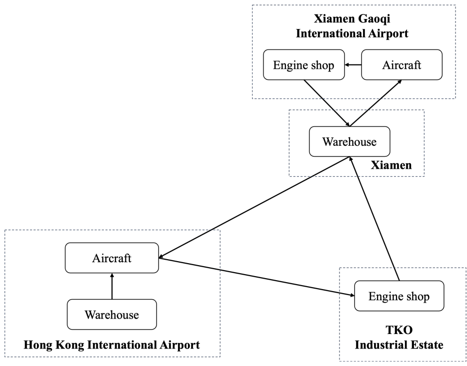

Figure 4.4: AEL of Case 2.

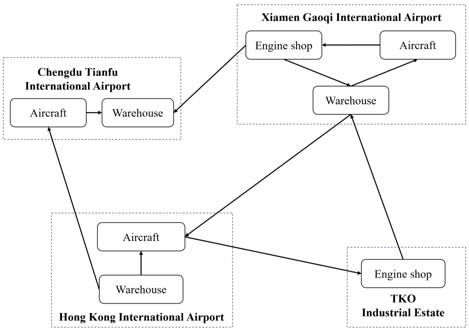

Figure 4.5: AEL of Case 3.

Using these demands as a basis, we then randomly generated a set of demands for Case 2 at XGIA. This means that the demands in Case 2 include those from both HKIA and XGIA. For each high demand set, the daily demand can range from 0 to 2 units. Specifically, there is a one-third probability of receiving 1 demand per day and a one-third probability of receiving 2 demands per day. The daily demands in Medium level range from 0 to 1 unit per day, with a one-half probability of the demand being 1 unit. For each low demand set, the daily demand can range from 0 to 1 unit. Specifically, there is a one-tenth probability of receiving 1 demand per day. Besides, we also randomly generate the demand change events for regular demands, and several emergency demands during the plan execution processes.

4.6.2 Performance Evaluation of RH-E Method

Given the cases and data discussed above, the experiments have been conducted using the RH-E method. All the programmes are developed using Python and the solutions for the static scheduling model in each decision point is solved by CPLEX. The results are shown in Table 4.2 and Table 4.4. In the tables, 'OC' refers to 'operation cost' while 'TC' refers to 'total cost'. In traditional dynamic scheduling method, since no switching cost is considered, its 'TC' is the same with 'OC'. However, for smoothed decisions, 'TC' is the sum of 'OC'

Table 4.2: Sensitivity Analysis of Control Horizons with High Demand Level
(cost is measured in 1,000 HKD)

Control Horizon (day)	Case 1			Case 2			Case 3		
	Traditional	Smooth		Traditional	Smooth		Traditional	Smooth	
	OC	OC	TC	OC	OC	TC	OC	OC	TC
7	43000	43000	43003	84723	84723	84734	238022	238647	238662
8	43000	43000	43003	84723	84723	84735	238610	239107	239120
9	43000	43000	43002	84723	84723	84733	**237190**	**237947**	**237957**
10	43000	43000	43006	**84543**	**84543**	**84555**	238238	240363	240374
11	43000	43000	43006	84633	84633	84645	237888	239113	239124
12	43000	43000	43005	84723	84723	84733	237888	239203	239214
13	42910	42910	42915	84723	84723	84731	238428	238563	238574
14	**42820**	**42820**	**42825**	84633	84633	84641	238068	239113	239124
15	42910	42910	42915	84723	84723	84731	237798	238383	238394
16	43000	43000	43005	84723	84723	84731	237618	239113	239124
17	**42820**	**42820**	**42825**	84723	84723	84732	237978	239023	239034
18	43000	43000	43005	84723	84723	84732	237998	238843	238854
19	43000	43000	43005	84723	84723	84732	237708	238843	238854
20	43000	43000	43005	84723	84723	84732	237618	238563	238574
21	43000	43000	43005	84723	84723	84732	237618	238563	238574

and the switching cost.

For both the scheduling methods considering switching cost or not, we have tested the performance with different control horizons, from 7 days to 21 days, in all the cases with high, medium and low demand levels. Counter-intuitively, the control horizon is not always the shorter the better. Our findings indicate that most scenarios achieve their best performance with a control horizon of around 7 or 14 days. This is likely because the maintenance time for an engine is set at 7 days, which has a significant relationship with and impact on the optimal decision cycles.

4.6.3 Performance Evaluation of Smoothed Decisions

To evaluate the impact of smoothed decision-making, this part compares the operation costs of AEL in three demand levels, as shown in Table 4.2, Table 4.3, and Table 4.4.

From the results, it can be found that considering switching cost in engine scheduling will not affect the operation costs too much in most cases. Surprisingly, in cases with higher complexity and lower demands, the smoothed decision-making can lead to cost savings. When demand is low, there may be sufficient resources available to prepare for tasks in

Table 4.3: Sensitivity Analysis of Control Horizons with Medium Demand Level
(cost is measured in 1,000 HKD)

Control Horizon (day)	Case 1			Case 2			Case 3		
	Traditional	Smooth		Traditional	Smooth		Traditional	Smooth	
	OC	OC	TC	OC	OC	TC	OC	OC	TC
7	25820	25820	25825	50776	50776	50789	136544	**136215**	**136231**
8	25730	25730	25735	50686	50686	50699	**135644**	136300	136316
9	25820	25820	25825	50686	50686	50699	136184	137275	137291
10	25730	25730	25735	**50596**	**50596**	**50609**	136904	136549	136565
11	**25640**	**25640**	**25645**	50686	50686	50699	136130	137340	137356
12	25730	25730	25735	50686	50686	50699	135734	137340	137356
13	25820	25820	25825	**50596**	**50596**	**50609**	135950	137340	137356
14	25820	25820	25825	50686	50686	50699	135860	136800	136816
15	25730	25730	25735	**50596**	**50596**	**50609**	135860	136890	136906
16	25730	25730	25735	50686	50686	50699	136310	136980	136996
17	25820	25820	25825	50686	50686	50699	135860	137070	137086
18	25820	25820	25825	50686	50686	50699	136220	136890	136906
19	25910	25910	25915	50686	50686	50699	136310	137070	137086
20	25910	25910	25915	50686	50686	50699	136220	136890	136906
21	25820	25820	25825	50686	50686	50699	135770	136980	136996

Table 4.4: Sensitivity Analysis of Control Horizons with Low Demand Level
(cost is measured in 1,000 HKD)

Control Horizon (day)	Case 1			Case 2			Case 3		
	Traditional	Smooth		Traditional	Smooth		Traditional	Smooth	
	OC	OC	TC	OC	OC	TC	OC	OC	TC
7	**16310**	**16310**	**16312**	**25592**	**25886**	**25890**	59301	59441	59445
8	16400	16400	16402	26582	26696	26700	58931	59531	59535
9	16400	16400	16402	25612	26626	26630	58931	58951	58955
10	16400	16400	16402	25612	26626	26630	60491	59741	59745
11	16490	16490	16492	25882	26716	26720	61366	59162	59166
12	16580	16580	16582	25972	26806	26810	59426	58442	58446
13	16670	16670	16672	26062	26896	26900	59955	59331	59335
14	16760	16760	16762	26152	26986	26990	58886	59072	59076
15	16940	16940	16942	25882	26716	26720	60011	58892	58896
16	17030	17030	17032	26782	26896	26900	59666	**57647**	**57651**
17	17210	17210	17212	27052	27166	27170	58991	59717	59721
18	17300	17300	17302	26602	27436	27440	58901	59267	59271
19	17120	17120	17122	26602	27436	27440	**58787**	60387	60391
20	17300	17300	17302	27212	28046	28050	59417	58892	58896
21	17480	17480	17482	27392	28226	28230	60877	59712	59716

advance, which can increase the likelihood of wasted efforts. The smoothed decisions could avoid frequent changes of plans and ensure the well execution of engine schedule plans. However, in traditional dynamic decisions, the system may suffer from frequent changes of plans. Due to the long execution time at every step (the large time-lag after decisions), such changes will properly disrupt the execution of many scheduling plans, thus have relatively worse performance.

4.6.4 Managerial Implications

According to the above experimental results, several important managerial implications can be concluded as follows.

First, incorporating rolling-horizon and event-driven method is effective in coping with the uncertainties in aircraft engine scheduling, and could well handle the emergency demands. In practices, the airlines could consider using such method to integrate its decisions to further improve the efficiency and reduce the cost of aircraft engine scheduling.

Secondly, smoothed decisions can partially benefit the companies, not only on avoiding effort wastes and complains, but also could reduce operation cost and delays. The advantages will be more prominent in complex scenarios where the changes of plans may happen more frequently. Thus, it is suggested airlines, especially large airlines with many destinations, could well analyze the switching cost and take it into consideration for its dynamic decision processes.

4.7 Summary

Aircraft engine scheduling is an important issue in aviation but has not been well studied in literature. Motivated by real-life problems encountered in airlines, this chapter coordinate all the logistics decisions in AEL operation and proposes an dynamic scheduling method, RH-E method, that integrates rolling-horizon and event-driven strategies to cope with changes of regulars demands and the occurrence of emergency demands. Moreover, this work considers the switching cost of changing plans in the dynamic decision processes, and proposed smoothed dynamic decisions, which is proved effective in reducing the cost and delays with lower demands.

Chapter 5

Aircraft Engine Logistics Network Design with Off-Site Warehouse

5.1 Introduction

As the power component of aircraft, engine is critical to aviation industry. The combination of its characteristics such as high value and special safety requirements all contribute to the substantial logistics costs. In current practices, the AEL system continues to experience high logistics expenses burden, which imposes cost pressure for managers during decision-making. While the application of optimization methods can help improve the cost-effectiveness of AEL, its impact is limited by the inherently high transportation and holding cost level in the current AEL system. Therefore, it is crucial to explore cost reduction through network design perspective rather than simply optimizing existing processes.

The implementation of off-site warehouses has been widely adopted in some logistics network to study the effect of network structures on optimal decision-making, such as retailing logistics (Ding & Kaminsky, 2020; N. Li & Wang, 2023) and construction logistics (Xu et al., 2018, 2019). However, it is still open for discussion on whether an off-site warehouse can help this AEL scenario. Various considerations may underpin the choice of introducing an off-site warehouse, especially the demand levels and airline bases. The volume of demands in AEL is relatively irregular and intermittent (Huiskonen, 2001; Syntetos et al., 2012), and an off-site warehouse built outside and far from airports may induce additional transshipment of engines, which is usually of high cost as mentioned. Further investigations are still needed on the performance of off-site warehouse in AEL. And it is important to analyse the interaction mechanisms and potential impacts of these factors to strategically integrate the off-site warehouse into the AEL network and ensure its effectiveness.

Therefore, this chapter focuses on the analysis of the off-site warehouse in AEL through investigating its performance with different AEL scenarios and demand levels. The reminder of this chapter is organized as follows. Section 5.2 introduces the off-site warehouse and presents its application and development in current practices. Experimental case studies are conducted in Section 5.3 with managerial insights. Section 5.4 summarizes the work of this chapter.

5.2 Off-Site Warehouse in Aircraft Engine Logistics

Off-site warehouse refers to the storage facility located outside the demand regions with a lower land rent to save cost. It is a strategic network design for the stakeholders to optimize the logistics operations and improve the overall cost-effectiveness.

Although not formally defined in literature, such concept has been widely adopted in construction systems, especially in prefabricated construction cases (Bataglin et al., 2024; Xu et al., 2018, 2019), where the use of off-site warehouse is expected to effectively provide both time and space buffers in logistics operations to enhance flexibility and reduce congestion. Similarly, some studies on supply chain management have explored the use of off-site warehouse, for example, N. Li and Wang (2023) investigated the inventory control when introducing one warehouse based on multiple offline stores. Van Wingerden et al. (2019) introduces an emergency warehouse based on the existed central and local warehouses to manage the inventory of spare parts in a large network. Furthermore, the off-site warehouse has also been introduced to support the multimodal logistics system to increase the efficiency. A new sea-air multimodal transshipment mode was developed by Hong Kong International Airport (HKIA) for cargo consolidation and storage, with the expectation of reducing costs by 50% and handling time by approximately one-third (Dong et al., 2023). The exports from the mainland can be handled in HKIA Logistics Park in Dongguan before being transported by sea to the airport cluster for air transshipment to worldwide destinations. This logistics park serves a similar function to that of an off-site warehouse.

In addition to the introduce of off-site warehouse, inventory sharing and pooling is another inventory management strategy to enhance operational efficiency. In aircraft maintenance industry, the spare parts management is fundamental and takes up about 13% of the total operating cost (Gu et al., 2015). Inventory pooling for aircraft spare parts is proved to be an effective way to improve a company's logistics performance, and the optimal stocking level within the complete pooling of stock among the hubs and air companies was studied by Wong et al. (2005). By collaborating with multiple airlines to share spare parts inventory resources, it can help reduce holding costs, improve maintenance resource availability, and respond more effectively to demand fluctuations. In practices, China Aviation Supplies Holding Company provides an aviation spare parts sharing platform for its clients, aiming to establish a new spare parts support system for aviation and optimize resource allocation (China Aviation Supplies Corporation, 2024). KN SparesChain also utilizes regional distribution hubs and consignment stock to provide spare parts and reduce costs with inventory planning, control and optimization (Nagel, 2024).

With the aforementioned cases and studies on off-site warehouses in various industries, as well as the inventory pooling and sharing of aircraft spare parts, it is worth discussing the effectiveness of aircraft engine inventory sharing based on the off-site warehouse in AEL. Furthermore, it is necessary to explore the conditions under which this approach may be beneficial and how the demand levels influence its effectiveness.

5.3 Experimental Case Study

Expensive on-site engine storage near the airport drives the airlines to utilize an off-site warehouse with lower holding costs. However, this may introduce another cost consideration - the high expense of transporting the engines to and from the off-site warehouse. In this section, several experimental case studies are conducted based on the engine scheduling methods of Chapter 4 to investigate the performance of the off-site warehouse and engine inventory sharing with two scenarios and demand levels. Then, several managerial implications are discussed.

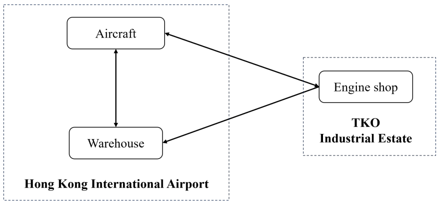

Figure 5.1: AEL of Scenario 1-Case A.

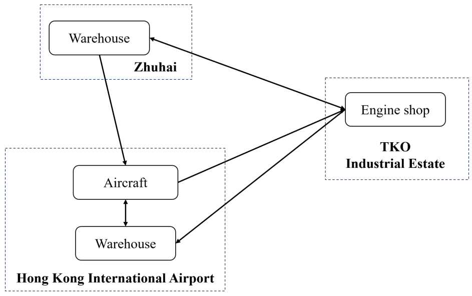

Figure 5.2: AEL of Scenario 1-Case B.

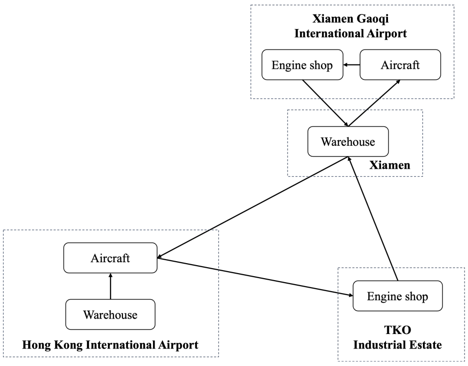

Figure 5.3: AEL of Scenario 2-Case A.

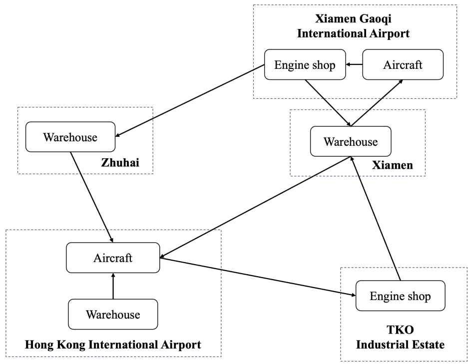

Figure 5.4: AEL of Scenario 2-Case B.

5.3.1 Scenario Description

Six experimental cases are developed based on the scenario in Hong Kong, as depicted in Figure 5.1 to Figure 5.6. Scenario 1-Case A (Figure 5.1) is the basic scenario that only contains one demand node, one warehouse, and one engine shop. Here, the demand node and warehouse are located in HKIA while the engine shop is located in TKO industrial estate of Hong Kong, which is around 50 km from HKIA. Adding an off-site warehouse located in Zhuhai to Scenario 1-Case A, Case B (Figure 5.2) is developed. Here, the off-site warehouse is only around 90 km from HKIA and has lower holding cost than that in HKIA. Compared with Scenario 1, Scenario 2 (Figure 5.3) includes Xiamen Gaoqi International Airport (XMN), which has one demand node, and one engine shop, and also includes one warehouse in Xiamen. Based on Scenario 2-Case A, Case B (Figure 5.4) also adds an off-site warehouse at Zhuhai. In this case, the off-site warehouse could serve HKIA and XMN simultaneously and the engine inventory is shared by HKIA and XMN. In addition, Chengdu Tianfu International Airport (TFU) is included in Scenario 3 (Figure 5.5), which serve as one demand node and one warehouse. Similarly, an off-site warehouse at Zhuhai is added in its Case B (Figure 5.6).

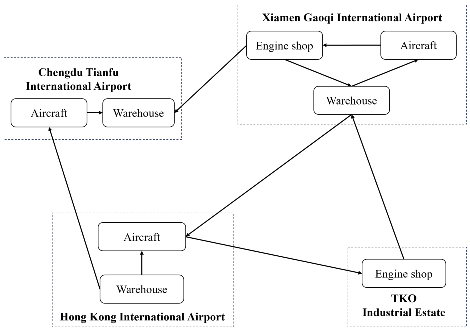

Figure 5.5: AEL of Scenario 3-Case A.

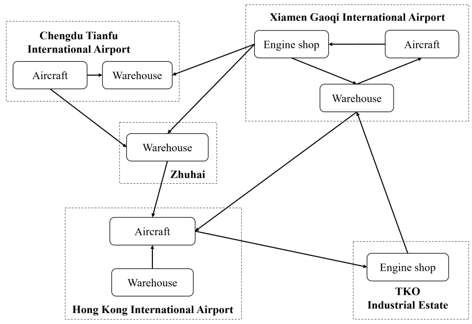

Figure 5.6: AEL of Scenario 3-Case B.

In all the six cases, the holding costs per engine per day in Hong Kong, Xiamen, Chengdu, and Zhuhai are set as HKD \$1421, \$228, \$200 and \$150 respectively. The transportation cost for one engine per kilometer is HKD \$71. Without loss of generality, the planning horizon in all experiments are set as 30 days, maintenance time for each engine is 7 days, and the total studied period is 1 year (365 days). Align with industrial practices, the control horizon is set in the range from 7 to 21 days.

We randomly generated three sets of ERM demands with different demand levels (high, medium, and low) for Scenario 1, 2, 3, respectively. The daily demands in high demand level are range from 0 to 2 units. Specifically, there is a one-third probability of receiving 1 demand per day and a one-third probability of receiving 2 demands per day. The daily demands in Medium level range from 0 to 1 unit per day□with a 50% probability of the demand being 1 unit. And the daily demand in low demand level is only with a one-tenth probability of 1 unit per day. Besides, we randomly generated demand change events for regular demands and emergency demands during the study period.

5.3.2 Effectiveness of Off-site Warehouse

In this part, experiments have been conducted to investigate the effectiveness of adopting an off-site warehouse for efficient aircraft engine scheduling. The results are shown in Figure 5.7, Figure 5.8, and Figure 5.9. The total cost ratio refers to the operation cost in each Case B (with off-site warehouse) to the operation cost in each Case A (without off-site warehouse).

From the results, it can be found the effectiveness of off-site warehouse is not so obvious in most cases, especially for relatively simple scenarios (Scenario 1 and Scenario 2). However, for relatively complex scenario, e.g., Scenario 3, savings of operation cost can be found, especially for cases with low demand level. This may be due to the relatively low

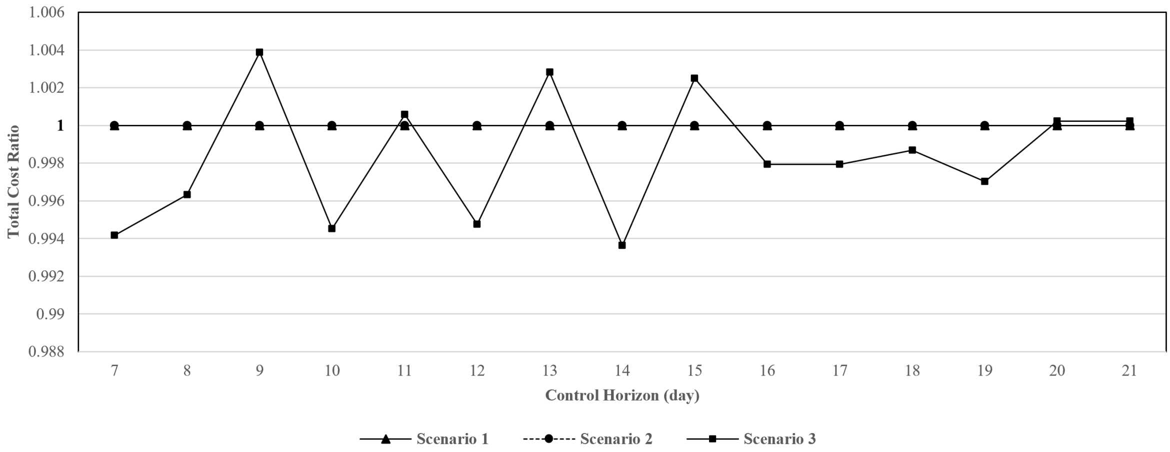

Figure 5.7: Total Cost Ratio with High Demand Level.

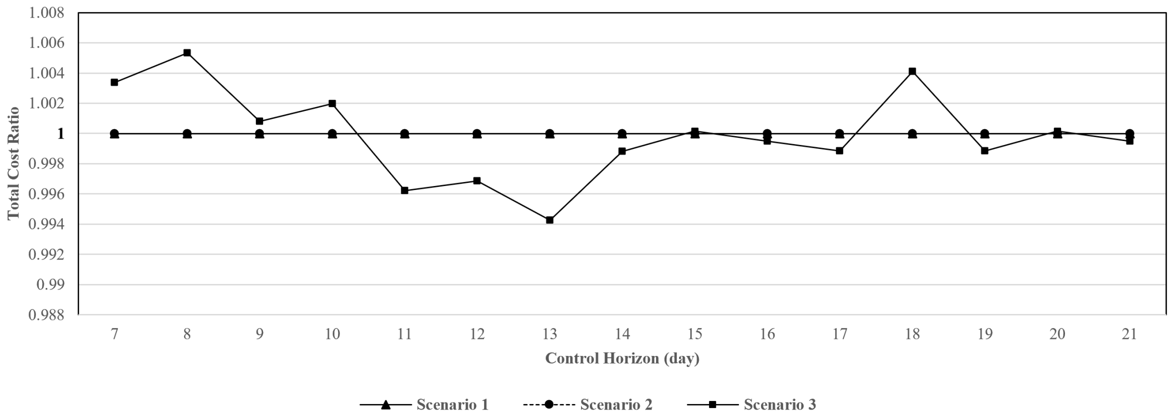

Figure 5.8: Total Cost Ratio with Medium Demand Level.

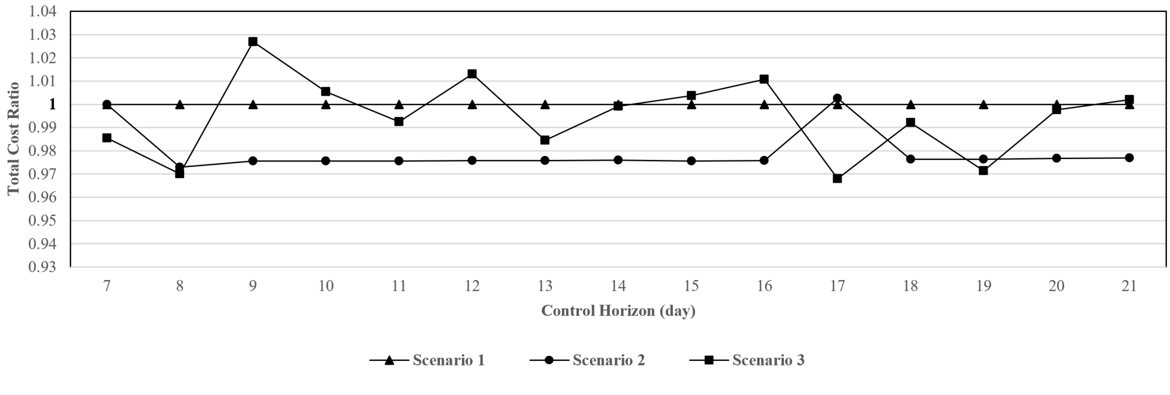

Figure 5.9: Total Cost Ratio with Low Demand Level.

number of engines requiring storage, coupled with high transportation costs, which offset the benefit of low holding cost.

5.3.3 Managerial Implications

According to the above experimental results, several important managerial implications can be concluded as follows.

Off-site warehouse is effective in saving the cost of AEL and could improve the ability to cope with disturbances. Specifically, it is more effective when the holding cost difference is large. In practices, the operation managers should recognize that the effectiveness of off-site warehouse strategy and the engine inventory sharing is closely tied to demand levels. High demand creates the conditions necessary to yield significant benefits. It suggests that if the off-site warehouse can be shared among more airlines and engine shops to undertake more engine demands, the cooperation may lead to profit gains for the whole industry. In such a scenario, it could potentially achieve positive social welfare outcomes and a ”win-win” situation for all stakeholders involved.

5.4 Summary

Given the inherently high cost structure of the AEL system due to the characteristics of aircraft engines, this chapter aims to enhance efficiency and reduce operational costs from a network design perspective by introducing off-site warehouse into the AEL network. Based on the scheduling method proposed in Chapter 4, the experiments were conducted to verify the effectiveness of off-site warehouse and analyse its performance on cost saving and reducing delays. It is found that the effectiveness of the off-site warehouse is closely related to engine demand levels. In practices, the airlines are encouraged to collaborate in sharing engine inventory based on leveraging the use of off-site warehouses, as greater collaboration leads to improved benefits.

Chapter 6

Conclusion

6.1 Achievements

The objective of this study is to develop smoothed decision-making methods and strategies to realize cost-effective AEL, with the consideration of uncertain demands. This are achieved by two main works.

First, the aircraft engine scheduling is an important issue in aviation but has not been well studied in literature. Motivated by real-life problems encountered in airlines, the first work proposed an dynamic scheduling method for aircraft engines. The operation process and decisions involved in aircraft engine scheduling were analyzed first, then an integrated decision-making model was developed to coordinate all the decisions in different steps. After that, an dynamic scheduling method, RH-E method, that integrates rolling-horizon and event-driven strategies was developed to cope with changes of regulars demands and the occurrence of emergency demand. Specifically, this work considered the switching cost of changing plans in the dynamic decision processes, and proposed smoothed dynamic decisions, which is proved to be effective in reducing the cost and delays with low demands.

To reduce the operation cost of AEL, the off-site warehouse was introduced to explore cost reduction through network perspective rather than simply optimizing existing processes limited by the inherently cost level in the current AEL system. The effectiveness of off-site warehouse was verified in reducing costs and the delays with lower demands and more complex scenario. And it is also suggested based on the experiment results that the cooperation of more airlines to use the warehouse and share the engine inventory may lead to profit gains for the whole industry.

6.2 Future Works

In the future, this work can be extended in three streams. First, the uncertainties in aircraft engine maintenance maintenance processes and engine transportation can be considered. The maintenance time is uncertain due to the highly dependence on maintenance personnel, specific spare parts and tools. And the engine transportation may be effected by the traffic and weather conditions and specific vehicle required. Taking these into considering in research may further improve the efficiency of AEL.

Besides, the scenarios with heterogeneous engines can be explored in future research, which is more in line with industry practices. Such exploration may help improve the airlines' competitiveness in a rapidly evolving market.

Moreover, it is still need to analyze several critical factors from a theoretical perspective, including holding cost differentials, transportation levels, maintenance time, and capacity. Understanding the impact mechanism of these variables on engine scheduling in AEL will provide valuable insights and contribute to more effective decision-making processes.

References

Ahmed, M. B., Mansour, F. Z., & Haouari, M. (2018). Robust integrated maintenance aircraft routing and crew pairing. *Journal of Air Transport Management*, *73*, 15–31.

Alomari, Y., Andó, M., & Baptista, M. L. (2023). Advancing aircraft engine rul predictions: An interpretable integrated approach of feature engineering and aggregated feature importance. *Scientific Reports*, *13*(1), 13466.

Al-Thani, N. A., Ahmed, M. B., & Haouari, M. (2016). A model and optimization-based heuristic for the operational aircraft maintenance routing problem. *Transportation Research Part C: Emerging Technologies*, *72*, 29–44.

Australian Aaviation. (2014). Emirates complete first a380 heavy check [https://australianaviation.com.au/2014/11/emirates-completes-first-a380-heavy-check/, Last accessed on 13th Sept 2024].

Barenji, A. V., Wang, W., Li, Z., & Guerra-Zubiaga, D. A. (2019). Intelligent e-commerce logistics platform using hybrid agent based approach. *Transportation Research Part E: Logistics and Transportation Review*, *126*, 15–31.

Başdere, M., & Bilge, Ü. (2014). Operational aircraft maintenance routing problem with remaining time consideration. *European Journal of Operational Research*, *235*(1), 315–328.

Bataglin, F. S., Formoso, C. T., & Viana, D. D. (2024). Slack categories for managing risks in the delivery and assembly of engineer-to-order prefabricated building systems. *IEEE Transactions on Engineering Management*.

Batalha, E. d. C. P. (2012). *Aircraft engines maintenance costs and reliability: An appraisal of the decision process to remove an engine for a shop visit aiming at minimum maintenance unit cost* [Doctoral dissertation].

Baumol, W. J., & Wolfe, P. (1958). A warehouse-location problem. *Operations research*, *6*(2), 252–263.

Cai, L., Li, W., Luo, Y., & He, L. (2023). Real-time scheduling simulation optimisation of job shop in a production-logistics collaborative environment. *International Journal of Production Research*, *61*(5), 1373–1393.

Cakmak, E., & Guney, E. (2023). Spare parts inventory classification using neutrosophic fuzzy edas method in the aviation industry. *Expert Systems with Applications*, *224*, 120008.

Cardeal, G., Leite, M., & Ribeiro, I. (2023). Decision-support model to select spare parts suitable for additive manufacturing. *Computers in Industry*, *144*, 103798.

Chen, N., Comden, J., Liu, Z., Gandhi, A., & Wierman, A. (2016). Using predictions in online optimization: Looking forward with an eye on the past. *ACM SIGMETRICS Performance Evaluation Review*, *44*(1), 193–206.

Chen, N., Goel, G., & Wierman, A. (2018). Smoothed online convex optimization in high dimensions via online balanced descent. *Conference On Learning Theory*, 1574–1594.

Chen, Q., Li, M., Xu, G., & Huang, G. Q. (2023). Cyber-physical spare parts intralogistics system for aviation mro. *Advanced Engineering Informatics*, *56*, 101919.

Chen, R., Cheng, T., Ng, C., Wang, J.-Q., Wei, H., & Yuan, J. (2024). Rescheduling to trade off between global disruption of original jobs with flexibility and scheduling cost of new jobs. *Omega*, *128*, 103114.

Chen, Y., Zhao, Q., Wang, L., & Dessouky, M. (2016). The regional cooperation-based warehouse location problem for relief supplies. *Computers & Industrial Engineering*, *102*, 259–267.

China Aviation Supplies Corporation, C. (2024). Pooling of aircraft material [http://www.casc.com.cn/cas/en/?page_id=85, Last accessed on 20th Oct 2024].

Chung, K.-J., Her, C.-C., & Lin, S.-D. (2009). A two-warehouse inventory model with imperfect quality production processes. *Computers & Industrial Engineering*, *56*(1), 193–197.

CNN. (2024). Cathay pacific inspects entire a350 fleet after finding engine problems [https://edition.cnn.com/2024/09/02/business/hong-kong-cathay-pacific-a350-hnk-intl/index.html,Last accessed on 20th Oct 2024].

Costantino, F., Di Gravio, G., Patriarca, R., & Petrella, L. (2018). Spare parts management for irregular demand items. *Omega*, *81*, 57–66.

Cui, R., Dong, X., & Lin, Y. (2019). Models for aircraft maintenance routing problem with consideration of remaining time and robustness. *Computers & Industrial Engineering*, *137*, 106045.

Díaz-Ramírez, J., Huertas, J. I., & Trigos, F. (2014). Aircraft maintenance, routing, and crew scheduling planning for airlines with a single fleet and a single maintenance and crew base. *Computers & Industrial Engineering*, *75*, 68–78.

Ding, S., & Kaminsky, P. M. (2020). Centralized and decentralized warehouse logistics collaboration. *Manufacturing & Service Operations Management*, *22*(4), 812–831.

Dinis, D., Barbosa-Póvoa, A., & Teixeira, Â. P. (2019). A supporting framework for maintenance capacity planning and scheduling: Development and application in the aircraft mro industry. *International Journal of Production Economics*, *218*, 1–15.

Dong, W., Qiu, X., & Xu, G. (2023). Scheduled transport service design for cross-border logistics in airport cluster. *30th ISTE International Conference on Transdisciplinary Engineering: Leveraging Transdisciplinary Engineering in a Changing and Connected World, TE 2023*, 363–372.

Eltoukhy, A. E., Chan, F. T., Chung, S. H., & Niu, B. (2018). A model with a solution algorithm for the operational aircraft maintenance routing problem. *Computers & Industrial Engineering*, *120*, 346–359.

Eltoukhy, A. E., Wang, Z., Chan, F. T., Chung, S. H., Ma, H.-L., & Wang, X. (2019). Robust aircraft maintenance routing problem using a turn-around time reduction approach. *IEEE transactions on systems, man, and cybernetics: Systems*, *50*(12), 4919–4932.

Gallego-García, S., Gejo-García, J., & García-García, M. (2021). Development of a maintenance and spare parts distribution model for increasing aircraft efficiency. *Applied Sciences*, *11*(3), 1333.

Gandhi, A., Harchol-Balter, M., & Adan, I. (2010). Server farms with setup costs. *Performance Evaluation*, *67*(11), 1123–1138.

Goel, G., & Wierman, A. (2019). An online algorithm for smoothed regression and lqr control. *The 22nd International Conference on Artificial Intelligence and Statistics*, 2504–2513.

Gu, J., Zhang, G., & Li, K. W. (2015). Efficient aircraft spare parts inventory management under demand uncertainty. *Journal of Air Transport Management*, *42*, 101–109.

Gu, J., Goetschalckx, M., & McGinnis, L. F. (2007). Research on warehouse operation: A comprehensive review. *European Journal of Operational Research*, *177*(1), 1–21.

Gui, Y., Zhang, Z., Tang, D., Zhu, H., & Zhang, Y. (2024). Collaborative dynamic scheduling in a self-organizing manufacturing system using multi-agent reinforcement learning. *Advanced Engineering Informatics*, *62*, 102646.

Hamidi, M. R., Gholamian, M. R., Shahanaghi, K., & Yavari, A. (2017). Reliable warehouse location-network design problem under intentional disruption. *Computers & Industrial Engineering*, *113*, 123–134.

Hasni, M., Aguir, M., Babai, M. Z., & Jemai, Z. (2019). Spare parts demand forecasting: A review on bootstrapping methods. *International Journal of Production Research*, *57*(15-16), 4791–4804.

Ho, G. T., Tang, Y. M., Tsang, K. Y., Tang, V., & Chau, K. Y. (2021). A blockchain-based system to enhance aircraft parts traceability and trackability for inventory management. *Expert Systems with Applications*, *179*, 115101.

Hu, Q., Boylan, J. E., Chen, H., & Labib, A. (2018). Or in spare parts management: A review. *European Journal of Operational Research*, *266*(2), 395–414.

Hu, Y., Miao, X., Zhang, J., Liu, J., & Pan, E. (2021). Reinforcement learning-driven maintenance strategy: A novel solution for long-term aircraft maintenance decision optimization. *Computers & industrial engineering*, *153*, 107056.

Huang, Y., Ding, Y., Hao, K., & Jin, Y. (2017). A multi-objective approach to robust optimization over time considering switching cost. *Information Sciences*, *394*, 183–197.

Huiskonen, J. (2001). Maintenance spare parts logistics: Special characteristics and strategic choices. *International Journal of Production Economics*, *71*(1-3), 125–133.

Jin, Y., Tang, K., Yu, X., Sendhoff, B., & Yao, X. (2013). A framework for finding robust optimal solutions over time. *Memetic Computing*, *5*, 3–18.

Kang, Y., Lee, S., & Do Chung, B. (2019). Learning-based logistics planning and scheduling for crowdsourced parcel delivery. *Computers & industrial engineering*, *132*, 271–279.

Kenzhevayeva, Z., Katayeva, A., Kaikenova, K., Sarsembayeva, A., Babai, M., Tsakalerou, M., & Papadopoulos, C. (2021). Inventory control models for spare parts in aviation logistics. *Procedia Manufacturing*, *55*, 507–512.

Kilpi, J., Töyli, J., & Vepsäläinen, A. (2009). Cooperative strategies for the availability service of repairable aircraft components. *International Journal of Production Economics*, *117*(2), 360–370.

Kinnison, H. A., & Siddiqui, T. (2013). Aviation maintenance management.

Kleywegt, A. J., Nori, V. S., & Savelsbergh, M. W. (2004). Dynamic programming approximations for a stochastic inventory routing problem. *Transportation Science*, *38*(1), 42–70.

Kraft, J., & Kuntzagk, S. (2017, June). *Engine Fleet-Management: The Use of Digital Twins From a MRO Perspective* (Vol. Volume 1: Aircraft Engine; Fans and Blowers; Marine; Honors and Awards). https://doi.org/10.1115/GT2017-63336

Lee, C. C., & Hsu, S.-L. (2009). A two-warehouse production model for deteriorating inventory items with time-dependent demands. *European Journal of Operational Research*, *194*(3), 700–710.

Li, N., & Wang, Z. (2023). Inventory control for omnichannel retailing between one warehouse and multiple stores. *IEEE Transactions on Engineering Management*, *71*, 7395–7412.

Li, X., Dekker, R., Heij, C., & Hekimoğlu, M. (2016). Assessing end-of-supply risk of spare parts using the proportional hazard model. *Decision Sciences*, *47*(2), 373–394.

Li, Y., Qu, G., & Li, N. (2020). Online optimization with predictions and switching costs: Fast algorithms and the fundamental limit. *IEEE Transactions on Automatic Control*, *66*(10), 4761–4768.

Liang, Z., & Chaovalitwongse, W. A. (2013). A network-based model for the integrated weekly aircraft maintenance routing and fleet assignment problem. *Transportation Science*, *47*(4), 493–507.

Liang, Z., Chaovalitwongse, W. A., Huang, H. C., & Johnson, E. L. (2011). On a new rotation tour network model for aircraft maintenance routing problem. *Transportation Science*, *45*(1), 109–120.

Liang, Z., Feng, Y., Zhang, X., Wu, T., & Chaovalitwongse, W. A. (2015). Robust weekly aircraft maintenance routing problem and the extension to the tail assignment problem. *Transportation Research Part B: Methodological*, *78*, 238–259.

Liang, Z., Xiao, F., Qian, X., Zhou, L., Jin, X., Lu, X., & Karichery, S. (2018). A column generation-based heuristic for aircraft recovery problem with airport capacity constraints and maintenance flexibility. *Transportation Research Part B: Methodological*, *113*, 70–90.

Lin, M., Liu, Z., Wierman, A., & Andrew, L. L. (2012). Online algorithms for geographical load balancing. *2012 international green computing conference (IGCC)*, 1–10.

Lin, M., Wierman, A., Andrew, L. L., & Thereska, E. (2012). Dynamic right-sizing for power-proportional data centers. *IEEE/ACM Transactions on Networking*, *21*(5), 1378–1391.

Lin, M., Wierman, A., Roytman, A., Meyerson, A., & Andrew, L. L. (2012). Online optimization with switching cost. *ACM SIGMETRICS Performance Evaluation Review*, *40*(3), 98–100.

Lu, T., Chen, M., & Andrew, L. L. (2012). Simple and effective dynamic provisioning for power-proportional data centers. *IEEE Transactions on Parallel and Distributed Systems*, *24*(6), 1161–1171.

Ma, H.-L., Sun, Y., Chung, S.-H., & Chan, H. K. (2022). Tackling uncertainties in aircraft maintenance routing: A review of emerging technologies. *Transportation Research Part E: Logistics and Transportation Review*, *164*, 102805.

Maher, S. J., Desaulniers, G., & Soumis, F. (2014). Recoverable robust single day aircraft maintenance routing problem. *Computers & Operations Research*, *51*, 130–145.

Michel, L., & Van Hentenryck, P. (2004). A simple tabu search for warehouse location. *European Journal of Operational Research*, *157*(3), 576–591.

Mookherjee, R., Hobbs, B. F., Friesz, T. L., & Rigdon, M. A. (2008). Dynamic oligopolistic competition on an electric power network with ramping costs and joint sales constraints. *J. Ind. Manag. Optim*, *4*(3), 425–452.

Nagel, K. (2024). Kn spareschain – your aerospace aftermarket supply chain partner [https://be.kuehne-nagel.com/en/-/services/industry/aerospace/kn-spares-chain, Last accessed on 20th Oct 2024].

Ngai, E. W., Cheung, B. K., Lam, S., & Ng, C. T. (2014). Rfid value in aircraft parts supply chains: A case study. *International Journal of Production Economics*, *147*, 330–339.

Ngai, E., Cheng, T., Lai, K.-h., Chai, P., Choi, Y., & Sin, R. (2007). Development of an rfid-based traceability system: Experiences and lessons learned from an aircraft engineering company. *Production and Operations Management*, *16*(5), 554–568.

Ortega, E. J. A., Malicki, S., Doerner, K. F., & Minner, S. (2024). Stochastic inventory routing with dynamic demands and intra-day depletion. *Computers & Operations Research*, *163*, 106503.

Ozsen, L., Coullard, C. R., & Daskin, M. S. (2008). Capacitated warehouse location model with risk pooling. *Naval Research Logistics (NRL)*, *55*(4), 295–312.

Parmentier, A., & Meunier, F. (2020). Aircraft routing and crew pairing: Updated algorithms at air france. *Omega*, *93*, 102073.

Qin, X., Jiang, Z.-Z., Sun, M., Tang, L., & Liu, X. (2021). Repairable spare parts provisioning for multiregional expanding fleets of equipment under performance-based contracting. *Omega*, *102*, 102328.

Qin, Y., Ma, H.-L., Chan, F. T., & Khan, W. A. (2020). A scenario-based stochastic programming approach for aircraft expendable and rotable spare parts planning in mro provider. *Industrial Management & Data Systems*, *120*(9), 1635–1657.

Qin, Y., Ng, K. K., & Sun, X. (2024). Service accessibility strategy for aircraft maintenance routing with interorganizational collaborations on outsourcing maintenance. *Computers & Industrial Engineering*, *190*, 110071.

Rath, S., & Gutjahr, W. J. (2014). A math-heuristic for the warehouse location–routing problem in disaster relief. *Computers & Operations Research*, *42*, 25–39.

Regattieri, A., Gamberi, M., Gamberini, R., & Manzini, R. (2005). Managing lumpy demand for aircraft spare parts. *Journal of Air Transport Management*, *11*(6), 426–431.

Ren, J., Cheng, Y., Zhang, Y., & Tao, F. (2024). A digital twin-enhanced collaborative maintenance paradigm for aero-engine fleet. *Frontiers of Engineering Management*, 1–6.

Roh, S., Pettit, S., Harris, I., & Beresford, A. (2015). The pre-positioning of warehouses at regional and local levels for a humanitarian relief organisation. *International Journal of Production Economics*, *170*, 616–628.

Rolls-Royce. (2024a). Rolls-royce wins engine order from cathay pacific for 60 trent 7000 engines [https://www.rolls-royce.com/media/press-releases/2024/07-08-2024-poweroftrent-rr-wins-engine-order-from-cathay-pacific-for-60-trent-7000-engines.aspx, Last accessed on 7th Sept 2024].

Rolls-Royce. (2024b). Totalcare [https://www.rolls-royce.com/media/our-stories/discover/2017/totalcare.aspx, Last accessed on 7th Sept 2024].

Ruan, J., Wang, Z., Chan, F. T., Patnaik, S., & Tiwari, M. K. (2021). A reinforcement learning-based algorithm for the aircraft maintenance routing problem. *Expert Systems with Applications*, *169*, 114399.

Saltzman, R. M., & Stern, H. I. (2022). The multi-day aircraft maintenance routing problem. *Journal of Air Transport Management*, *102*, 102224.

Sarac, A., Batta, R., & Rump, C. M. (2006). A branch-and-price approach for operational aircraft maintenance routing. *European Journal of Operational Research*, *175*(3), 1850–1869.

Sheikh-Zadeh, A., Farhangi, H., & Rossetti, M. D. (2020). Inventory grouping and sensitivity analysis in multi-echelon spare part provisioning systems. *Computers & Industrial Engineering*, *143*, 106230.

Shi, G., Lin, Y., Chung, S.-J., Yue, Y., & Wierman, A. (2020). Online optimization with memory and competitive control. *Advances in Neural Information Processing Systems*, *33*, 20636–20647.

Shi, Y., Guo, X., & Yu, Y. (2018). Dynamic warehouse size planning with demand forecast and contract flexibility. *International Journal of Production Research*, *56*(3), 1313–1325.

Singh, V. P., & Ganguly, K. K. (2022). A supporting framework for estimating trade-off between cost and availability at equipment level: Development and application in the aircraft mro industry. *Production Planning & Control*, 1–16.

Sweeney, D. J., & Tatham, R. L. (1976). An improved long-run model for multiple warehouse location. *Management Science*, *22*(7), 748–758.

Syntetos, A. A., Babai, M. Z., & Altay, N. (2012). On the demand distributions of spare parts. *International Journal of Production Research*, *50*(8), 2101–2117.

Tanaka, M. (2006). Real-time pricing with ramping costs: A new approach to managing a steep change in electricity demand. *Energy Policy*, *34*(18), 3634–3643.

Topan, E., Eruguz, A. S., Ma, W., van der Heijden, M. C., & Dekker, R. (2020). A review of operational spare parts service logistics in service control towers. *European Journal of Operational Research*, *282*(2), 401–414.

Van der Heide, G., Buijs, P., Roodbergen, K., & Vis, I. (2018). Dynamic shipments of inventories in shared warehouse and transportation networks. *Transportation Research Part E: Logistics and Transportation Review*, *118*, 240–257.

Van Wingerden, E., Tan, T., & Van Houtum, G.-J. (2019). The impact of an emergency warehouse in a two-echelon spare parts network. *European Journal of Operational Research*, *276*(3), 983–997.

van Jaarsveld, W., Dollevoet, T., & Dekker, R. (2015). Improving spare parts inventory control at a repair shop. *Omega*, *57*, 217–229.

Vincent, F. Y., Salsabila, N. Y., Siswanto, N., & Kuo, P.-H. (2022). A two-stage genetic algorithm for joint coordination of spare parts inventory and planned maintenance under uncertain failures. *Applied Soft Computing*, *130*, 109705.

Wang, B. C., Qian, Q. Y., Gao, J. J., Tan, Z. Y., & Zhou, Y. (2021). The optimization of warehouse location and resources distribution for emergency rescue under uncertainty. *Advanced Engineering Informatics*, *48*, 101278.

Wang, R., Qin, Y., & Sun, H. (2021). Research on location selection strategy for airlines spare parts central warehouse based on metric. *Computational Intelligence and Neuroscience*, *2021*.

Wen, X., Sun, X., Ma, H.-L., & Sun, Y. (2022). A column generation approach for operational flight scheduling and aircraft maintenance routing. *Journal of Air Transport Management*, *105*, 102270.

Wong, H., Cattrysse, D., & Van Oudheusden, D. (2005). Stocking decisions for repairable spare parts pooling in a multi-hub system. *International journal of production economics*, *93*, 309–317.

Wu, L.-J., Shi, L., Zhan, Z.-H., Lai, K.-K., & Zhang, J. (2022). A buffer-based ant colony system approach for dynamic cold chain logistics scheduling. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *6*(6), 1438–1452.

Xu, G., Li, M., Chen, C.-H., & Wei, Y. (2018). Cloud asset-enabled integrated iot platform for lean prefabricated construction. *Automation in Construction*, *93*, 123–134.

Xu, G., Li, M., Luo, L., Chen, C.-H., & Huang, G. Q. (2019). Cloud-based fleet management for prefabrication transportation. *Enterprise Information Systems*, *13*(1), 87–106.

Yan, S., Yang, T.-H., & Chen, H.-H. (2004). Airline short-term maintenance manpower supply planning. *Transportation Research Part A: Policy and Practice*, *38*(9-10), 615–642.

Yang, H.-L. (2004). Two-warehouse inventory models for deteriorating items with shortages under inflation. *European Journal of Operational Research*, *157*(2), 344–356.

Yazdani, D., Branke, J., Omidvar, M. N., Nguyen, T. T., & Yao, X. (2018). Changing or keeping solutions in dynamic optimization problems with switching costs. *Proceedings of the Genetic and Evolutionary Computation Conference*, 1095–1102.

Zhao, Y., Zhao, Q., Zhang, X., Zhu, E., Liu, X., & Yin, J. (2020). Understand dynamic regret with switching cost for online decision making. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *11*(3), 1–21.

Zheng, J., Wang, L., Wang, L., Wang, S., Chen, J.-F., & Wang, X. (2022). Solving stochastic online food delivery problem via iterated greedy algorithm with decomposition-based strategy. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *53*(2), 957–969.

Zhou, H., Farsi, M., Harrison, A., Parlikad, A. K., & Brintrup, A. (2023). Civil aircraft engine operation life resilient monitoring via usage trajectory mapping on the reliability contour. *Reliability Engineering & System Safety*, *230*, 108878.

Zhou, H., Parlikad, A. K., & Brintrup, A. (2022). Data-driven maintenance priority recommendations for civil aircraft engine fleets using reliability-based bivariate cluster analysis. *Quality Engineering*, 1–16.

Zhou, Y. W., & Yang, S. L. (2005). A two-warehouse inventory model for items with stock-level-dependent demand rate. *International Journal of Production Economics*, *95*(2), 215–228.

Zhu, S., van Jaarsveld, W., & Dekker, R. (2022). Critical project planning and spare parts inventory management in shutdown maintenance. *Reliability Engineering & System Safety*, *219*, 108197.