AIR LOGISTICS OPERATIONS: CABIN CREW SCHEDULING AND RISK ANALYSIS

WEN XIN

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The Hong Kong Polytechnic University

Department of Industrial and Systems Engineering

Air Logistics Operations: Cabin Crew Scheduling and Risk Analysis

WEN Xin

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

______________________________(Signed)

______WEN Xin_______________(Name of student)

Abstract

The air logistics industry is playing a crucial role in the modern world through facilitating both passenger and cargo movement nationally and internationally. However, this industry is characterized by fierce competition, high operating costs, and diverse uncertainties. Therefore, air logistics operators are committed to improving decision quality for both passenger and cargo logistics to maintain profitability in the risky and competitive market. Among the air logistics management issues, the operational scheduling problems for air passenger logistics and strategic pricing strategies for air cargo logistics are the critically important and challenging decisions. Therefore, focusing on these two areas, this thesis aims at enhancing the operational and strategic decision making for modern airlines in the current volatile business environment. As cabin crews are crucial resources for airlines which are relatively under-studied compared to cockpit crews, this research firstly concentrates on improving the operational cabin crew scheduling methodologies by proposing a new practical pairing approach from the perspective of air passenger logistics operations. Then, the strategic risk-averse pricing decisions are investigated where the mean-variance theory is utilized for risk analysis from the perspective of air cargo logistics operations.

Regarding the air passenger logistics operations, cabin crew scheduling is one of the most important but challenging operational scheduling problems faced by airlines, which is decomposed into a cabin crew pairing problem and a cabin crew assignment problem. Due to the high complexity and large scale of the problem, cabin crews are usually scheduled on a team basis separated by aircraft types as cockpit crews for simplicity. However, the cross-qualification of cabin crews and the manpower configuration heterogeneity of various flights make the scheduling problem for cabin crews totally different from that for cockpit crews. Besides, some airlines are adopting the individual cabin crew pairing approach, and applying the strategy of controlled crew substitution to hedge against the manpower requirement variation caused by flight fluctuation in the uncertain market. Motivated by the emergence of individual cabin crew pairing practice as well as the shortcomings of the team-based cabin crew pairing scheme, this research conducts an analytical study which aims at improving

manpower utilization while reducing costs by utilizing a new individual cabin crew pairing generation approach. The impacts of the relationship between manpower availability with requirement benchmarks on cabin crew scheduling strategies are investigated to derive deep insights regarding airline crew management in the volatile market. A customized column generation approach is developed to solve the problem. Computational experiments based on real-world collected flight schedules data demonstrate the advantages of the proposed approach over the existing team-based method, such as substantially improving manpower utilization by 199% and reducing cost by 61%. Furthermore, the proposed pairing approach shows great potential in alleviating the negative impact of flight fluctuation.

On the other hand, the strategic pricing decisions for air cargo carriers are extremely challenging due to the intensive market competition and diverse uncertainties arising from both market demand and operating costs. However, this problem is rather under-explored in the literature. It is reasonable that many freight airlines are holding risk-averse attitudes in decision making in order to survive in the highly volatile and competitive market. Therefore, in this thesis, the mean-variance theory is applied to characterize the risk-averse behaviors of decision makers, and the equilibrium prices for two competing risk-averse air cargo carriers under demand and cost uncertainties are derived. Then, how the crucial factors like risk sensitivity coefficients, market competition, market share, demand uncertainty and cost uncertainty affect the airlines' optimal prices is studied. In addition, important cost thresholds and relative risk-averse attitude thresholds are identified for the impacts of these factors on the equilibrium prices. The analytical results derived from this research demonstrate the symmetry in the optimal prices and critical thresholds for the two carriers. Besides, the importance to consider both carrier's own and the competitor's risk attitudes and operating characteristics in decision making when market competition exists is highlighted. Moreover, the direct and indirect impacts of risk attitudes on the optimal prices are identified, thus highlighting the importance to integrate risk considerations into the optimal pricing decision framework. Finally, it is found that market situations play a critical role in characterizing the effects of diverse parameters on the equilibrium prices, which should be carefully evaluated by decision makers.

To conclude, realizing the importance of improving the decision making for air logistics operations in the highly uncertain and competitive market, this research conducts the series of research described in this thesis. Specifically, a new individual cabin crew pairing generation approach which demonstrates superior performances in manpower utilization improvement and cost reduction for air passenger logistics operations is developed. Moreover, this study also conducts an analytical risk analysis for air cargo logistics operations, and explores the optimal pricing strategies for freight airlines facing diverse uncertainties through the application of the mean-variance theory. The insights derived from this thesis research not only contribute to the air logistics management literature, but they also provide valuable guidance to practitioners such as operations managers in airlines.

Peer-Refereed Journal Publications Derived from this PhD Study

1. **Wen, X.**, Chung, S.-H., Ji, P., Sheu, J.-B., & Choi, T. M. (2019). Multi-Class Cabin Crew Pairing Problems with Controlled Crew Substitution in Airline Operations. *Transportation Research Part B: Methodological*, under the second round review.
2. **Wen, X.**, Xu, X., Choi, T. M., & Chung, S.-H. (2019). Optimal Pricing Decisions of Competing Air-Cargo-Carrier Systems – Impacts of Risk Aversion, Demand and Cost Uncertainties. *IEEE Transactions on Systems, Man and Cybernetics: Systems*, forthcoming.
3. Choi, T. M., **Wen, X.,** Sun. X.T., & Chung, S.-H. (2019). The Mean-Variance Approach for Global Supply Chain Risk Analysis with Air Logistics in the Blockchain Technology Era. *Transportation Research Part E: Logistics and Transportation Review*, 127, 178-191.
4. **Wen, X.**, Choi, T. M., & Chung, S.-H. (2019). Fashion Retail Supply Chain Management: A Review of Operational Models. *International Journal of Production Economics*, 207, 34-55.
5. **Wen, X.**, Ma, H.-L., Choi, T. M., & Sheu, J.-B. (2019). Impacts of the Belt and Road Initiative on the China-Europe trading route selections. *Transportation Research Part E: Logistics and Transportation Review*, 122, 581-604.
6. Choi, T. M., Chung, S.-H., Sun. X.T., & **Wen, X.** (2019). How do Blockchain Technologies Enhance Co-opetitive Buffer Stock Sharing Schemes? *Working paper*.

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Chapter 1. Introduction

1.1. Background of Study

1.1.1. The Air Logistics Industry

The air logistics industry is playing an important role in the modern world through facilitating both passenger and cargo movement nationally and internationally (Başar & Bhat, 2004). According to International Air Transport Association (IATA), 3.8 billion air passengers have spent almost 650 billion US dollars in 2016 (IATA 2017a), and air passenger demand is predicted to reach 8.2 billion passengers per year in 2037 (IATA 2018b). Besides, the annual global statistics of International Civil Aviation Organization (ICAO) show that the number of worldwide flight departures reached 36.7 million in 2017, achieving a 3.1% growth compared to 2016. On the other hand, air cargo logistics occupies a substantial share of the whole freight logistics service sector, and air-cargo carrier systems are an important part of the transportation logistics systems. Due to the increased global trades, higher demand for fast shipment, and companies' efforts in keeping low inventory level through quick and frequent replenishments (Li et al., 2017a; Li et al., 2017b), the air freight transportation industry is growing rapidly in recent years. According to IATA (2016), in 2015, air logistics delivered over 6 trillion US dollars' worth of cargos, accounting for 35% of international trade of value. Besides, it is reported that the industry-wide revenue of air freight transportation reaches 95.9 billion US dollars in 2017, achieving a remarkable growth of 18.69% compared to the year of 2016, while the global air freight tonne kilometers (FTKs) increased by 9.0% in 2017, which is the highest growth rate since 2010 (IATA, 2017b). Moreover, in the next twenty years, the volume of air freight is forecasted to continue its growth to be "double of today" (Airbus 2017). Currently, air cargo has become a crucial component of revenue not only for dedicated cargo air carriers (e.g., Cargolux), but also for combinatorial air carriers (e.g., Cathay Pacific)

(Feng et al., 2015).

However, despite the fast growth and increasing importance, the air logistics industry is facing diverse challenges. First of all, the industry is characterized by fierce and intensive market competition. For example, it is predicted that approximately 350 new-built air cargo carriers in North America and 200 in Asia-Pacific will appear in the next twenty years (Airbus, 2017; Boeing, 2017). For the passenger transport sector, economists demonstrate that the state of global airline competition has intensified in recent years, with more choices offered in the market when traveling from one city to another[1]. Second, the market is highly volatile and uncertain, with remarkable variations in consumer demand (Powell & Winston, 1983; Tao et al., 2017). As reported by the Civil Aviation Department of the Government of the Hong Kong Special Administration Region[2], the air passenger traffic volume keeps fluctuating throughout the year. For example, in the year of 2018, the minimum monthly air passenger traffic (both departure and arrival) is 5,539,901 passengers in September, while the maximum traffic is 6,817,626 in August. Regarding air cargo, IATA (2018a) reports that the monthly industry-wide freight traffic kept varying throughout the year of 2017, and the difference between the highest (in November) with the lowest (in February) volumes reaches around 5 billion FTKs. Third, as the fuel consumption comprises the largest part of an airline's operating costs, the fluctuation in crude oil price creates significant challenges for the profitability and development of air freight companies (Azadian & Murat, 2018; Chao & Hsu, 2014).

Consequently, airlines are fully committed to improving decision quality for both passenger and cargo logistics to maintain profitability (Sheu, 2014; Sheu & Li, 2014). With the objective of enhancing the operational and strategic decision making for modern airlines in the current volatile environment, this thesis research is established. First, considering the importance of cabin crews for air passenger logistics (which is detailed in Section 1.1.2), this PhD study concentrates on improving the pairing

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[1] https://www.aviationpros.com/airlines/article/12419680/driven-by-competition-the-airline-industry-is-taking-off (Retrieved in July, 2018).

[2] https://www.cad.gov.hk/english/statistics.html (Retrieved in July, 2019).

approach for airline cabin crews which can significantly increase manpower utilization and reduce operating costs (as presented in Chapter 3). Second, realizing the great challenges of pricing decisions for freight airlines (which is explained in Section 1.1.3), analytical research focusing on enhancing the pricing strategies by integrating risk considerations into the decision framework for air cargo logistics is conducted (as presented in Chapter 4).

1.1.2. Air Passenger Logistics Operations & Cabin Crew Scheduling

Air passenger transportation is a core functional component of modern airlines, in which cabin crews play a critical role in serving passengers and monitoring the safety of passengers during flights. To facilitate passenger logistics, airlines have to manage diverse resources (like cabin crews) smoothly and efficiently to maintain normal flight operations. In general, airline scheduling is usually divided into four sequential stages, namely flight scheduling, fleet assignment, aircraft maintenance routing, and crew scheduling (Liang et al., 2015; Mukherjee & Hansen, 2009; Pita et al., 2014; Şafak et al., 2018). Among these problems, crew scheduling is an important but challenging component which assigns crews to serve the scheduled flights with a minimum cost (Boubaker et al., 2010). Besides, crew scheduling is further divided into a crew pairing problem and a crew assignment problem. Crew cost is known as the second largest composition of an airline's total operating cost, just after fuel consumption. For example, a major Hong Kong based airline (denoted as The Airways), reports that 21% of its annual operating expenses are for manpower payment, which follows the biggest fuel cost (29.5%). Therefore, even a slight improvement in crew schedules can lead to a substantial cost saving (Cohn & Barnhart, 2003). Currently, there is little research studying the important cabin crew pairing problem with considerations of the distinctive characteristics of cabin crews. Therefore, in this thesis, Chapter 3 focuses on improving the financial performance of cabin crew scheduling decisions with an individual management system to enhance the decision making for air passenger logistics operations. In the following, firstly, the two-stage crew scheduling problem is introduced, followed by the comparison between cockpit crews and cabin crews. Next, an important practical operation of controlled crew substitution for cabin crews is described. Finally, the importance of the pairing problem for cabin crews is highlighted.

Crew scheduling: Crew pairing & crew assignment

Due to the extensive regulations imposed by airlines, labor unions, and authorities, and numerous possible itineraries, the "unmanageable" crew scheduling is generally fulfilled by sequentially solving a crew pairing problem (CPP) and a crew assignment problem (CAP) (Chung et al., 2017; Doi et al., 2018; Eltoukhy et al., 2017). Generally, short-haul and long-haul flights are scheduled separately. The CPP aims to generate sufficient anonymous legal pairings to cover all flights' requirements while minimizing costs under the assumption of infinite crews, usually for a week. A legal pairing is a sequence of flights to be served by the same crew while respecting all the regulations, which starts from and ends at the crew's home base (Wei & Vaze, 2018). Next, in the CAP, the pairings generated in the CPP are connected to form monthly schedules for specific crews with the consideration of crew availability and pre-scheduled activities such as training and vacations (Chung et al., 2015). Although such a rigidly separated sequential scheduling approach leads to a substantial reduction in problem complexity, the pairings generated in the CPP might not be suitable for the CAP, producing poor-quality outcomes (Quesnel et al., 2017). For example, Guo et al. (2006) state that failing to consider the crew availability constraint in the CPP can cause costly changes in the CAP, which leads to revisions of some generated pairings to identify a feasible solution. This thesis focuses on the single-based CPP for cabin crews and proposes a new pairing generation methodology to improve cabin crew utilization and reduce the related costs for air passenger logistics.

Two types of crews: Cockpit crew & cabin crew

There are two types of crews in airlines: cockpit crews and cabin crews (Bard & Mohan, 2008). A cockpit crew (pilot) is responsible for the duties essential to the operation of an aircraft, while a cabin crew is assigned with duties in the cabin for the interest of passengers' safety (ICAO, 2010). Generally, cockpit crews are classified into captain, first officer, and officer, qualified for only one type of aircraft (Sohoni et al., 2004). The manpower requirement for cockpit crews of a type of aircraft is deterministic according to the operations manual. Therefore, the cockpit CPP is decomposed and solved within each type of aircraft, and cockpit crews are scheduled as teams (Shebalov & Klabjan, 2006). Cabin crews are also categorized into multiple classes (e.g., stewards, hostesses, cabin mates, and head cabin mates) according to their skills and experiences to serve different cabin sections (Gamache et al., 1999). Traditionally, cabin crews are scheduled on a team basis separated by aircraft types as the way for cockpit crews. However, cabin crews are cross-qualified to serve multiple types of aircraft. Besides, even for the same aircraft type, the demand for cabin crews is not fixed due to various cabin layouts. For example, in The Airways, Airbus A330-300 has three types of layout, with 317, 262, and 251 seats in total respectively. Beyond the minimum requirements for the interest of passengers' safety regulated by aviation authorities and governments (e.g., at least one cabin crew for each pair of doors (IATA, 2015)), airlines usually establish higher service levels by assigning more cabin crews of each class to each flight based on the seating plan of the aircraft (Barnhart & Cohn, 2004). Therefore, the manpower requirement for each class of cabin crews is generally heterogeneous across aircraft types, flights, and airlines. Consequently, although the team-based cabin crew pairing approach could bring benefits like enhancing team spirits and reducing problem complexity, it inevitably leads to low manpower flexibility and utilization, and produces high costs. Realizing that the pairing problem for cabin crews is totally different from that for cockpit crews and the shortcomings of the existing method, The Airways[3] is currently adopting the individual pairing approach to enjoy the high manpower

[3] This finding is based on a discussion with the managers from a major Hong Kong based airline who choose to be anonymous, and this airline is denoted as "The Airways" in this thesis.

flexibility and utilization, and the resulting cost reduction, with the aim of maintaining profitability and competitiveness in a competition-intensive market. However, the problem scale and complexity of the individual cabin CPP are much higher than those of the traditional method.

An important cabin crew operation: Controlled crew substitution

Airlines usually operate a large-scale flight network. For example, The Airways is operating routes among 74 destinations around the world with hundreds of flights per day. Therefore, in order to make the problem manageable, The Airways divides the whole flight network into small regions, and conducts crew scheduling based on each divided region.[4] Consequently, although fleet composition variation is not an important problem for an entire flight network of an airline as aircrafts always stay in the airline for more than 20 years, it is a crucial factor for the divided flight networks. Moreover, instead of staying static, flight schedules are usually affected by the dynamic passenger demand and airline competition decisions (Hansen & Liu, 2015; Hsu & Wen, 2003; Vaze & Barnhart, 2012). Accordingly, flight schedules naturally fluctuate along time either in flight frequency or in aircraft types used (called flight fluctuation). For example, a flight from Hong Kong to Singapore this week might employ A330, but in the next week, it might use A350. Besides, The Airways might operate more flights for this route during the weeks in public holidays than normal weeks. Accordingly, flight fluctuation could lead to a variation in the requirements for cabin crews. Therefore, due to the finite availability, cabin crew insufficiency in some classes may occur during flight fluctuation. The Airways thus takes the strategy of Controlled Crew Substitution (CCS) to deal with the cabin crew shortage. CCS is to assign a cabin crew from another class to substitute the originally required one, with the aim of identifying feasible solutions when the current available manpower encounters a shortage in certain classes, in order to facilitate the normal operations of all flights. On the other hand, to maintain service and safety levels, at least one qualified cabin crew of each class should be

[4] This finding is based on a discussion with the managers from a major Hong Kong based airline who choose to be anonymous.

assigned to each flight. Additionally, unnecessary substitutions should be avoided when all classes are sufficient. The CCS strategy is an approach to hedge against the cabin crew requirement variation and manpower shortage led by flight fluctuation through the improvement of cabin crew utilization. However, it makes the cabin CPP even more difficult to deal with.

Importance of the pairing problem for cabin crews

Cabin crews are crucial for airlines in maintaining quality service levels and providing essential emergency and evacuation functions (ICAO, 2010). The significance of the professional conduct of cabin crews on flights has been emphasized in Chang and Yeh (2004). Besides, cabin crews nowadays constitute a major proportion of airline manpower with a significant climbing cost expenditure. For example, currently, 45.8% of the employees in The Airways are cabin crews, which is more than three times the cockpit crews (only 14.6%). More importantly, the inferior performance of the cabin crew pairing solutions can incur both expensive costs for airlines and great inconvenience for air passengers, leading to a significant damage to the image of airlines. For instance, recently, a flight from Sapporo to Hong Kong had to stop at Taipei, in order to change the cabin crews who violated the maximum duty period restriction regulated by the government[5]. This unexpected stopover resulted in a three-hour delay for 367 passengers. Therefore, the priority for airline crew scheduling departments is to efficiently manage this expensive resource and improve cabin crew utilization while reducing the related costs (Anbil et al., 1991; Salazar-González, 2014). However, despite the realized significance of cabin crews, relatively less research has focused on exploring the decision quality improvement of the cabin CPP compared to the cockpit CPP due to the high problem complexity.

[5] http://hk.on.cc/hk/bkn/cnt/news/20171217/bkn-20171217100546523-1217_00822_001.html (Retrieved in December, 2017).

1.1.3. Air Cargo Logistics Operations & Risk Analysis

There is no doubt that air cargo logistics plays a crucial role for modern airlines. It is reported that cargo transportation produces more than twice revenue than the first-class cabin passenger transport, and the throughput of air cargo grows 50% faster than that of air passenger (IATA, 2017b; Wong et al., 2009). However, under the highly volatile and competitive market environment, freight airlines are facing with diverse uncertainties, which create risks. In addition to demand, air cargo carriers are also challenged by uncertainties arising from costs. As reported by Airbus (2017), the international jet-fuel price kept fluctuating since 2000, which climbed by more than 200% from 2000 to 2008, followed by a sharp reduction by 50% in 2009. After that, the oil price grew rapidly to the 2008-level in 2010. Airbus (2017) has also predicted a great fluctuation in fuel price in the next two decades. Although some airlines adopt financial instruments like fuel hedging to alleviate the impact of oil price fluctuation, cost uncertainty still exists. For instance, Cathay Pacific is reported to lose 6.45 billion HK dollars in fuel hedging in 2017, causing great financial burden for the corporate.[6] Therefore, the significant uncertainties in operating costs should be carefully considered during decision making for cargo airlines. Consequently, it is seen that the strategic decisions of air cargo airlines are challenged by uncertainties from both demand and cost perspectives, together with intensive market competition. Therefore, it is reasonable that some freight airlines hold a risk-averse attitude against profit uncertainties to ensure themselves to be economically sustainable in the highly volatile and competitive environment.[7] As a result, enhancing the strategic decision making, especially with risk considerations, becomes crucial for air cargo logistics operations.

As pointed out by Azadian and Murat (2018), among the air logistics operations management issues (e.g., pricing problem, revenue management, capacity allocation), the pricing problem is the most important but challenging one. It is reported that modern

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[6] https://hongkongbusiness.hk/aviation/news/cathay-pacific-hit-massive-645b-fuel-hedging-loss-in-2017 (Retrieved in March, 2018).

[7] https://centreforaviation.com/analysis/reports/a350-1000-order-changes-pragmatism-prevails-as-airlines-become-more-risk-averse-370232 (Retrieved in October, 2017).

companies are keen to identify the optimal pricing decisions that enable them to adapt to the increasingly competitive market (He et al., 2014; Zhang et al., 2018). Although it has been identified that the objectives and equilibrium decisions[8] of risk-averse entities are totally different from those of risk-neutral ones (Chan et al., 2018), the optimal pricing decisions for competing risk-averse cargo airlines in the presence of demand and cost uncertainties are under-explored. Therefore, it is important and meaningful to explore such a problem and derive insightful managerial implications for air cargo logistics operators on how to enhance the competitiveness of freight airlines through investigating the impacts of risk aversion and market uncertainties on the equilibrium pricing decisions.

Risk analysis has become a crucial topic in operations management (Chen et al., 2007; Choi & Chiu, 2012b; Choi et al., 2016a, 2016b). Over the past few decades, different analytical models and measures have been proposed to help explore risks in operations and capture risk-averse behaviors (Keren & Pliskin, 2006). For example, CVaR (Chen et al., 2009), VaR (Chiu & Choi, 2010), semi-variance of profit (Choi & Chiu, 2012a), standard deviation of profit (Lau, 1980), variance of profit (Lau & Lau, 1999; Agrawal & Seshardri, 2000b; Vaagen & Wallace, 2008; Choi et al., 2011; Buzacott et al., 2011; Shen et al., 2013; Chiu et al., 2015), etc., have all been proposed. Among them, an increasing trend of using the mean-variance (MV) theory (Markowitz, 1959) for conducting risk analysis in operations management is observed (Chiu & Choi, 2016). In particular, the MV theory can be applied to help conduct analyses for operations management problems in two perspectives: 1. As an analytical measure for risk aversion and being included in the optimization objective. 2. As a performance measure to capture the profit risk of the associated operations. Both perspectives are meaningful, and have been extensively applied in operations management. Besides, the MV theory is widely used to solve risk-hedging problems which can provide practical and implementable solutions. Moreover, compared with other risk measurement tools, the MV theory is understandable by the practitioners. Therefore, in Chapter 4, the MV

[8] In this thesis, the terms “optimal” decision and “equilibrium” decision are used interchangeably.

theory is utilized to measure the risk-averse attitudes of cargo airlines in characterizing the crucial pricing strategies for air cargo logistics operations, with the consideration of demand and cost uncertainties under market competition.

1.2. Research Questions

Realizing the significance of both air passenger and air cargo logistics operations for airlines, and the extensive challenges faced by the industry, this thesis aims to solve the following research questions, with the objective of improving the operational and strategic decision making for air carriers.

First, regarding the air passenger logistics operations, this doctoral thesis research focuses on the important cabin CPP (presented in Chapter 3), tackling the following questions.

1. How to analytically model the distinctive characteristics of airline cabin crews in the pairing formulation?
2. How to deal with the flight requirement heterogeneity problem faced by airline cabin crew pairing problem?
3. How does the practical operation of controlled crew substitution affect the optimal pairing solutions?
4. How does the relationship between cabin crew availability levels with manpower requirement benchmarks impact cabin crew management?

Second, regarding the air cargo logistics operations, this study then aims to address the following research questions (presented in Chapter 4).

1. What are the optimal pricing decisions for two risk-averse air cargo carriers when they compete under stochastic demands?
2. How do the crucial factors (e.g., market competition, risk sensitivity coefficients, demand uncertainty, market share) affect the optimal prices?
3. What are the optimal prices if the two carriers face uncertain costs (e.g., related to the volatile oil prices)?
4. How does cost uncertainty influence the decision making of the two carriers?

1.3. Research Contributions

In this sub-chapter, the contributions of this research to the literature are summarized from two perspectives, air passenger logistics operations and air cargo logistics operations, in Section 1.3.1 and Section 1.3.2, respectively.

1.3.1. Air Passenger Logistics Operations

In Chapter 3 of the thesis, a novel individual cabin CPP approach is constructed for air passenger logistics operations (named Multi-class individual cabin crew pairing problem with availability and controlled crew substitution (MICCPP-ACCS)) which can greatly improve manpower utilization and reduce operating costs. The methodological characteristics and major contributions of the proposed models are outlined as follows.

Firstly, to overcome the ineffectiveness of most existing cabin CPP research with the single aircraft type assumption and team-based approach, this work follows the airline practice to model the multi-class cabin crews individually who can operate mixed types of aircraft with varying manpower demands. Such an individual modelling approach improves the flexibility of cabin crews, and captures the unique features of heterogeneous flights, with the aim of improving manpower utilization. More importantly, global optimality is maintained without separating the problem by aircraft types. Besides, it should be pointed out that optimization software is now provided for airlines to deal with the problem of flight requirement heterogeneity, which applies many copies of a flight, each of which stands for a person (or group of persons) needed. Although this approach is currently used by some airlines, it has been scarcely studied in the academic domain. However, the team-based pairing approach still occupies the main research stream. Consequently, the team-based pairing approach is applied as a benchmark to demonstrate the importance of modelling cabin crews individually and the advantages of the proposed models.

Secondly, this study proposes to consider the crew availability constraint in the CPP for each class of cabin crews, so as to relieve the drawback of the separated sequential scheduling approach to a certain extent. As discussed in Guo et al. (2006), failing to consider the crew availability limit in the CPP could lead to extra crew proceedings (like pairing breaking and reconstruction), which causes undesirable increased operating costs. The existing studies that consider manpower availability are primarily based on crew teams (e.g., Dunbar et al., 2014). In this work, an upper limit for cabin crew availability of each class during the planning horizon is imposed, in order to improve the pairing generation process and cabin crew utilization.

Thirdly, the proposed MICCPP-ACCS approach embeds the practical strategy of CCS into the model, and formulates it through a substitution penalty cost in the objective function, together with a set of substitution recording constraints, minimum satisfaction constraints, and total satisfaction constraints. This makes the model realistic and also different from the ones in the literature. When the current available manpower of each class is sufficient, the proposed MICCPP-ACCS acts as the simplified MICCPP-A (Multi-class individual cabin crew pairing problem with availability), to identify the least-cost “set of pairings” within each class to cover all flights’ requirements without any function of CCS. However, once there exists a manpower shortage in any class during flight fluctuation, the CCS strategy in MICCPP-ACCS will endeavor to sustain the normal operations of all flights by assigning cabin crews from other classes to substitute the originally required ones to form feasible solutions. This strategy significantly alleviates the impact of manpower variation and manpower shortage led by flight fluctuation on cabin crew management by raising cabin crew utilization. Therefore, the substitution penalty cost is also called the flight fluctuation coefficient. Through computational experiments based on real data, the CCS strategy has proven its crucial role in reducing the influence of flight fluctuation. Besides, extra cabin crew variables are introduced to ensure solution feasibility in case that the entire flight requirements could not be fully satisfied even with the application of CCS.

Fourthly, this work generates managerial insights about the relationship between the cabin crew availability levels with flight schedule manpower requirement benchmarks for airlines with the assistance of the proposed models. Specifically, MICCPP-ACCS and MICCPP-A can provide various manpower requirement benchmarks for flight schedules, like the minimum total manpower demand with CCS and the minimum manpower demand for each class without CCS. Through the analysis on the relationship between availability levels with the obtained benchmarks, knowledge regarding whether the current available manpower is in a shortage, and whether manpower substitution or extra manpower is needed could be derived, which can be utilized by the airline crew scheduling department to improve management decisions. To the best of our knowledge, such analysis on cabin crew availability levels has never been examined in the prior literature. This study is hence novel and makes an important contribution to the literature on airline transportation studies.

In summary, this doctoral thesis research contributes to the literature by proposing a new individual cabin crew pairing generation approach which simultaneously considers flight manpower requirement heterogeneity, manpower availability, and the strategy of controlled crew substitution. Besides, the implications brought by the manpower availability-requirement relationships are explored.

1.3.2. Air Cargo Logistics Operations

In Chapter 4 of the thesis, the risk-sensitive pricing strategies for air cargo logistics operations are examined. To the best of our knowledge, this research is the first analytical study that comprehensively explores how risk-aversion, market competition, demand uncertainty and cost uncertainty affect the optimal pricing decisions for air-cargo carrier operations. The incorporation of risk sensitivity in decision making is critically important. It helps to derive novel insights and implications regarding the impact of risk considerations on the pricing mechanisms for air cargo carriers. The mean-variance theory is applied to model the risk-averse behaviors of decision makers. Besides, cost uncertainty is considered, which provides useful information for practitioners to deal with the volatility arising from the crude oil market. All results are derived in closed-form and proven mathematically. Considering the importance of optimal price decisions for cargo airlines and the increasing attention from both academia and industry, this study provides crucial managerial implications to advance the understanding on the optimal pricing decisions for the air cargo logistics industry, and helps enhance the competitiveness of air cargo carriers in the highly uncertain market.

Moreover, it should be pointed out that the "risk analysis" in the thesis title refers to exploring both the risks arising from the cabin crew pairing problem (e.g., flight fluctuation, manpower shortage), and the profit uncertainty risks faced by the air cargo carrier operations (e.g., the profit risks derived from both the cost (from oil price variation) and demand volatilities).

1.4. Thesis Organization

This thesis is organized as follows. First, Chapter 2 comprehensively reviews the related literature from four aspects. Then, Chapter 3 builds a novel individual pairing approach for airline cabin crews with the aim of improving manpower utilization and reducing operating costs from the perspective of air passenger logistics management. Next, the optimal pricing strategies for cargo airlines with risk considerations measured by the mean-variance theory are investigated in Chapter 4 in order to improve the decision making for air cargo logistics management. Lastly, concluding remarks and potential future research directions of this thesis are given in Chapter 5. Besides, the parameters and variables used in Chapter 3 are summarized in Appendix A. The input data and operational parameters which facilitate the computational experiments of Chapter 3 are listed in Appendix B, while Appendix C gives some complementary materials for the computational analysis of Chapter 3. Moreover, the parameters and mathematical proofs for Chapter 4 are shown in Appendix D and Appendix E, respectively.

Chapter 2. Literature Review

In this chapter, firstly, the literature regarding air passenger logistics operations is reviewed in Section 2.1. To be specific, the four sequential airline scheduling stages are reviewed in Section 2.1.1. Then, the important two-stage airline crew scheduling problem is introduced in Section 2.1.2, while the four research streams of the CPP are stated in Section 2.1.3. Next, the analytical research on air cargo logistics operations, especially the essential pricing strategies, are reviewed in Section 2.2. Besides, as this research aims to integrate risk considerations into the decision framework, the analytical operations research with risk considerations is surveyed in Section 2.3. Specifically, Section 2.3.1 reports the risk management literature for air cargo logistics, while Section 2.3.2 gives an overview about the pricing strategies with risk considerations. Finally, the application of the mean-variance theory for risk analysis with air logistics from four aspects is reviewed in Section 2.4.

2.1. Air Passenger Logistics Operations

2.1.1. Airline Scheduling Problem

The air passenger logistics industry has experienced an increase in the awareness of effective and efficient operational strategies since the late 1950s (Barnhart et al., 2003a). The development of operations research (OR) has made considerable contributions for airlines to maintain a profitable growth rate. Air passenger logistics operations planning is very challenging, considering the stochastic passenger demand, hundreds of flights per day, different types of fleet, restrictions of airports and gates, air congestion, aircraft maintenance requirements, and abundant rules and regulations imposed by governments and labor unions. It is impractical to formulate and solve the whole scheduling problem in a single model due to the potential billions of constraints and decision variables. Consequently, decomposition of the uncontrollable problem into relatively smaller sequential problems becomes essential (Burke et al., 2010; Lan et al., 2006; Ball et al., 2007). Accordingly, the large-scale airline scheduling problem is generally solved by four consecutive sub-problems, i.e., flight scheduling, fleet assignment, aircraft maintenance routing, and crew scheduling. It should be pointed out that these decomposed problems are still on a large scale, with a high problem complexity. The formulation strategies and optimization approaches for each step are reviewed sequentially in the following.

2.1.1.1. Flight Scheduling

As the starting point of air passenger logistics operations planning, flight scheduling determines when to fly, where to fly, and the frequency of flights served for each particular market under competition. A typical flight schedule consists of flight number, arrival/departure time, and origin/destination. Flight schedule construction begins with traffic flow forecasting, and relies on manpower availability, operation features of fleet types, and government regulations.

Generally, the flight scheduling problem is solved by heuristic approaches. Yan et al. (2007) formulate it as a nonlinear integer programming problem and build an efficient heuristic algorithm for a Taiwan airline to help maintain its profitability in a competitive market. Yan and Young (1996) develop a strategy for the draft flight schedule modification problem which is modeled as a multiple commodity network flow problem, and construct a Lagrangian Relaxation based heuristic solution algorithm. However, this strategy is inefficient considering its unreasonable complexity and unsatisfactory computation time. Therefore, a two-phase method is incorporated into the model of Yan and Young (1996) for higher efficiency by Yan and Tseng (2002). These research studies assume a static situation and ignore potential perturbations. With the development of stochastic modeling approaches, airlines are capable to consider the uncertain passenger demand in the flight scheduling procedure. Therefore, schedules with higher efficiency and reliability can be produced. For instance, Lee et al. (2007) develop a multi-objective genetic algorithm to improve the robustness of flight schedules by adjusting the departing times according to real-time information.

2.1.1.2. Fleet Assignment

A typical flight schedule, as an output of the flight scheduling step, provides information about flight number, departure time, origin, arrival time, and destination. An appropriate aircraft type will then be assigned to each individual flight during the fleet assignment step. As stated by Rexing et al. (2000), the primary objective of fleet assignment is to maximize the capture / recapture rate of passengers and marginal revenue while minimizing total costs. The total flight costs consist of operating costs, passenger spill costs and potential deadhead costs.

The main constraints for fleet assignment are flight coverage, aircraft balance, and aircraft capacity. The key issue in the problem is to track the locations of aircraft at any time. Accordingly, a time-space network is developed by Hane et al. (1995) to achieve such a track. In this work, the fleet assignment problem is formulated as a large-scale multiple commodity network flow problem with side constraints, and a combinatorial optimization algorithm is proposed to solve the problems of degeneration and long computation times, which is proved to be faster than the traditional Linear Programing method by more than two orders of magnitude. Since then, great improvements in the quality of fleet assignment plans have been implemented. For example, Rushmeier and Kontogiorgis (1997) claim that USAir could achieve savings of at least 15 million dollars annually by applying their model. Similarly, a basic fleet assignment model with a time window identifies a $67,000 reduction in the daily costs for a major airline in the US (Rexing et al., 2000).

2.1.1.3. Aircraft Maintenance Routing

The flight network is decomposed into several sub-networks after the fleet assignment plan has been completed. Each sub-network is associated with a fleet type. In the step of aircraft maintenance routing, a sequence of flights (routing) in each sub-network is assigned to an aircraft from the related fleet type, while satisfying the maintenance requirements together with the flight coverage and aircraft availability constraints (Desaulniers et al., 1997b). Particularly, the flights in a routing should follow the rule that the destination of one flight is the same as the origin of the next flight. Additionally, a routing starts and ends at the same maintenance station, while each aircraft should visit a maintenance station during the regulated time interval along each routing.

Network circulation with side constraints is generally employed to solve the aircraft maintenance routing problem (Barnhart & Cohn, 2004). In the related literature, Sriram and Haghani (2003) propose a maintenance scheduling model for a middle-size airline aiming at minimizing the maintenance costs, and develop a heuristic approach to solve it in satisfactory computation times. Bartholomew-Biggs et al. (2003) compare the performances of a deterministic method with two searching methods for the aircraft routing problem based on real data. In the work of Sarac et al. (2006), a novel operational aircraft routing problem with comprehensive resource availability constraints and maintenance requirements is formulated. A branch-and-price approach with customized branching rules shows high solution efficiency when combined with a heuristic routing selection system.

2.1.1.4. Airline Crew Scheduling

As the last step of air passenger logistics operations planning, crew scheduling determines which crew from which home base to fly which flight, while satisfying numerous rules and regulations. Home bases are cities or stations where a crew is actually located (Aydemir-Karadag et al., 2013).

Salaries for airline crew are much higher than their counterparts in other transportation modes like railways. The expenditure on crews, which is reported to reach $1.3 billion annually for major U.S. airlines, takes up the second largest part of the total operating costs for airlines. Therefore, even a slight improvement in crew scheduling can bring dramatic savings (Hoffman & Padberg, 1993). Additionally, there are enormous rules and regulations imposed by governments, airlines, and labor agreements that crews should follow (e.g., the maximum elapsed time of a pairing, the maximum flying hours allowed, and the maximum number of flights in a duty). Combined with the flight coverage constraints and the cost minimization requirement, crew scheduling remains a challenge for OR researchers.

Due to its significance and complexity, the crew scheduling optimization problem has been investigated by many researchers for decades (e.g. Levine, 1996; Cordeau et al., 2001; Borndörfer et al., 2006). Ball (2003) point out that integer programming (IP), one of the most important techniques in operations research, has achieved one of its first applications on this problem. Furthermore, research on crew scheduling has motivated the early development of the set-partitioning and set-covering problem. Most airlines have implemented IP-based crew scheduling systems to construct crew schedules by the end of 1980s. Arabeyre et al. (1969) provide the earliest overview about the work on crew scheduling. More surveys on crew scheduling problems can be found in Desaulniers et al. (1998), Barnhart et al. (2003a), Barnhart et al. (2003b) and Barnhart and Cohn (2004).

It should be pointed out that the rules and regulations for crews vary across airlines. Therefore, the research on crew scheduling concentrates on particular cases instead of general applications. Besides, the ways of scheduling domestic and international flights are different. In the next part, the two-stage airline crew scheduling problem is reviewed in detail.

2.1.2. Two-Stage Airline Crew Scheduling Problem

As discussed, crew scheduling is typically decomposed into two sequential processes: a CPP and a CAP. Medard and Sawhney (2007) demonstrate the reasons for such a decomposition as follows.

i. Explosive numbers of variables and constraints are derived when the integrated problem is considered.
ii. The rules and regulations are generally divided into a pairing-phase category and an assignment-phase category from the aspect of planning time.

iii. The quality of a crew scheduling plan largely depends on costs. The pairing process considers all the costs that are associated with operating a flight schedule. However, the objective of the CAP is to find a balance between costs and the specific needs of crews.

In conclusion, decomposing the airline crew scheduling problem into two processes is essential. Detailed discussions are as follows.

2.1.2.1. Crew Pairing Problem

The CPP selects a subset from all feasible pairings to cover each flight at least once, with a minimum cost (Anbil et al., 1992). Consequently, this problem is generally formulated as a large scale *set-partitioning* or *set-covering problem*. In the model, each constraint represents a flight coverage restriction, while each decision variable determines whether to select a pairing.

However, the number of possible pairings is counted in billions for major airlines. In addition, the complicated non-linear crew costs are generally represented by a function of the total elapsed time, total flying hours, and the minimum guaranteed payment, which increases the complexity of the problem (Barnhart et al., 2003b). Although the problem remains a challenge, there has been increasing research interests for the optimization of crew pairings. The reason is that it directly affects the quality of crew schedules and further influences the total crew costs (Stojković, et al., 1998; Zeghal & Minoux, 2006).

As stated by Klabjan (2005), in the U.S., a three-stage method (daily problem, weekly problem, and monthly problem) is generally applied to solve the monthly CPP without the consideration of crew levels. In the first stage of the daily problem, flights that repeat at least four days per week are selected to generate daily pairings. Next, in the second stage, the impossible pairings produced in the first stage are broken. Then, the flights released, together with the flights repeating at least three weeks per month, are combined to generate weekly schedules. Lastly, in the monthly problem, the unexpected pairings produced in the second stage are disconnected and the flights in these broken pairings are released. In this stage, the set of flights to be paired includes all the remaining flights. The ultimate solution to the original monthly problem is the sum of pairings generated in all the three stages. Due to the reduction in the scale of the problem, the three-stage method is useful and efficient for the monthly pairing problem. Moreover, the pairings generated can significantly maintain regularity which benefits management and is preferred by crews. However, Saddoune et al. (2013) present two weaknesses of the three-stage method. One is that the first two stages are worthless when the flight schedule is irregular, while the other concern is that it is impossible to repeat the same flight number in a daily pairing due to formulation limitations. They also show that skipping the first stage can produce solutions with higher quality. Additionally, Barnhart et al. (2003b) point out that the weekly problem (where the schedules repeat every week) and dated problem (a couple of days in a month) are valuable to research. For many airlines, decision makers usually develop pairings for a time range of seven days (a week) (Desaulniers et al., 1997a).

2.1.2.2. Crew Assignment Problem

Following the crew pairing stage, the second process of crew scheduling is the CAP, where specific individual crews are assigned to *schedules*, a legal sequence of pairings connected by days-off (Barnhart et al., 2003b). The CAP applies a pairing-based network, where nodes are pairings or activities including ground duties, trainings, and reserved duties, while arcs connect two pairings or activities. In such a network, a source-sink path represents a possible schedule for an individual crew. Similarly, there are also many rules and regulations that schedules should follow. Different from the flight coverage constraints considered in the CPP, the CAP is constrained by the pairing coverage restriction and the crew availability constraint at each base. In addition to cost minimization, airlines also concern about the preferences and requests of crews, and attempt to seek a satisfactory balance between these two aspects in the CAP.

2.1.3. Crew Pairing Problem by Crew Categories

As discussed, there are two types of crews in airlines: cockpit crews and cabin crews. Besides, these two types of air crews are characterized with totally different features which should be considered separately during scheduling. In this part, the existing CPP literature for different types of air crews is reviewed. Specifically, Section 2.1.3.1 focuses on the works studying the cockpit CPP, while Section 2.1.3.2 reviews the studies which consider both cockpit and cabin crews. Moreover, Section 2.1.3.3 concentrates on reporting the works for the cabin CPP, and Section 2.1.3.4 identifies a research stream that treats air crews as a general category without specifying the specific class.

2.1.3.1. The Crew Pairing Problems for Cockpit Crews

In the first research stream, studies are concentrating on the pairing problems for cockpit crews (e.g., Chu et al., 1997; Marsten et al., 1979; Saddoune et al., 2012; Sandhu & Klabjan, 2007; Schaefer et al., 2005; Shebalov & Klabjan, 2006). In these works, the cockpit CPP is decomposed by the types of aircraft with the same manpower requirement configurations owing to the features of cockpit crews. Consequently, the challenges caused by flight requirement heterogeneity no longer exist in the cockpit CPP. Here, decision variables are formulated for cockpit crew team pairings in which team members can work together for the whole pairing (Vance et al., 1997b; Yan & Chang, 2002).

Most of the cockpit CPP research takes the assumption of infinite manpower, except Guo et al. (2006), Dunbar et al. (2014), Stojković and Soumis (2001), and Yildiz et al. (2017). For example, Dunbar et al. (2014) impose an upper bound on the number of cockpit crew teams used when dealing with an aircraft routing-crew pairing integrated problem. Recently, Yildiz et al. (2017) propose to integrate the manpower fatigue factor into the crew pairing process for pilots, considering the severe outcomes it can lead to. The Three Process Model of Alertness is applied to formulate the fatigue level for pilots based on the so-called homeostatic and circadian processes. Moreover, crew availability is considered by modelling decision variables for each individual pilot. Interestingly, Yildiz et al. (2017) illustrate that with the application of the Three Process Model of Alertness, some of the existing rules and regulations imposed by authorities and airlines can be omitted.

2.1.3.2. The Crew Pairing Problems for Cockpit Crews & Cabin crews

This stream solves the pairing problem for both cockpit crews and cabin crews, which is further divided into two sub-streams. The first sub-stream, with the majority of research, applies the same modelling approach for the two types of crews, ignoring the distinctive characteristics of cabin crews (e.g., AhmadBeygi et al., 2009; Anbil et al., 1991; Dunbar et al., 2012; Erdoğan et al., 2015; Hoffman & Padberg, 1993; Muter et al., 2013; Salazar-González, 2014). Specifically, cabin crews are assumed to fly only a single type of aircraft and modelled as teams like cockpit crews, while the flight coverage constraint is to cover each flight (at least) once. Accordingly, the varying requirements among heterogeneous flights and the multiple classes of cabins crews are ignored. Therefore, the cabin CPP is much simplified and easier to solve in this sub-stream (Saddoune et al., 2013; Shao et al., 2017; Tekiner et al., 2009; Weide et al., 2010; Yen & Birge, 2006). However, this scheduling approach is inconsistent with the characteristics of cabin crews and the emerging airline practice. The flexibility of cabin crews is greatly restricted by being scheduled bundling with teams. Besides, the solution obtained this way is only locally optimal with respect to the separated problem by aircraft types. More importantly, the solution efficiency and cabin crew utilization are significantly impaired because the flight requirement heterogeneity is not considered. Moreover, in this sub-stream, most research ignores the manpower availability constraint expect Desaulniers et al. (1997a), Graves et al. (1993), and Stojković et al. (1998). The second sub-stream, with only one piece of related research (Medard & Sawhney, 2007), treats the two types of crews differently. Medard and

Sawhney (2007) recognize the flight requirement heterogeneity when making pairings for cabin crews. The so-called crew-need vectors are proposed to incorporate the varying flight requirements into the model. However, the authors formulate cabin crews as crew-slices (a form of team), rather than individuals, without the availability limit.

2.1.3.3. The Crew Pairing Problems for Cabin Crews

The third stream focuses on the CPP for cabin crews, with only two research works. For the first work, similar to the first sub-stream of the second stream, Yan and Tu (2002) build cabin crew team pairings to cover homogeneous flights without identifying the differences among multiple classes and manpower availability limitation. Differently, the second work, Yan et al. (2002), considers the various flight requirements across aircraft types of a Taiwan airline when making pairings for each class of cabin crews individually. Besides, Yan et al. (2002) use higher class cabin crews to substitute lower class ones. To the best of our knowledge, Yan et al. (2002) is the only literature that models cabin crews individually and crew substitution. However, the crew substitution in Yan et al. (2002) is random and uncontrolled where unnecessary substitutions cannot be avoided. Besides, it is not guaranteed that at least one qualified cabin crew from the required class is assigned to each flight. Furthermore, their model ignores the manpower availability constraints.

2.1.3.4. The Crew Pairing Problems for General Crews

The papers in the fourth stream consider the pairing problem for air crews. However, they do not specify whether “cockpit” crews or “cabin” crews are considered. Instead, they use the term of “crew” in a general sense. For instance, Chung et al. (2017) combine big data technology with the CPP to improve the robustness of solutions for crews, while Quesnel et al. (2017) consider an extended CPP where each crew base is constrained by total working time. In this stream, the distinctive characteristics of cabin crews are not considered in the pairing models. Besides, only homogeneous flights are considered and the infinite general crews are scheduled as teams without recognition of specific classes, which makes this stream similar to the research on cockpit crews. Many other studies belong to this stream (e.g., Barnhart & Shenoi, 1998; Barnhart et al., 1995; Cacchiani & Salazar-González, 2017; Cohn & Barnhart, 2003; Cordeau et al., 2001; Gao et al., 2009; Klabjan et al., 2001a, 2001b; Klabjan et al., 2002; Lavoie et al., 1988; Lettovský et al., 2000; Levine, 1996; Makri & Klabjan, 2004; Mercier & Soumis, 2007; Mercier et al., 2005; Papadakos, 2009; Ruther et al., 2017)

2.2. Air Cargo Logistics Operations

2.2.1. Analytical Research for Air Cargo Logistics

As an important part of air logistics, air cargo transportation has become increasingly critical to the success of global supply chains. However, in the literature, the majority of airline-related analytical operations research concentrates on passenger transport (Chen & Chou, 2017; Chung et al., 2017; Doi et al., 2018; Liang et al., 2018; Wei & Vaze, 2018), while much less explores air cargo transportation (Wang et al., 2017). Most of the existing literature on air freight operations investigates the topics like revenue management, capacity management, entry decisions, and booking control. For instance, Barz and Gartner (2016) construct heuristics for network air freight revenue management based on linear programming, decomposition and approximate dynamic programming, while Wada et al. (2017) investigate the capacity allocation problem for risk-averse cargo airlines. From the perspective of market entry decisions, Wang et al. (2017) study an air freight service supply chain with promised delivery time competition. The authors identify the win-win and lose-lose situations for both mainline carriers and regional carriers if the mainline carriers enter the upstream regional market. They also find that the multi-dimensional competition could reduce the negative impact of the upstream entry on the incumbent regional carriers. On the other hand, Hellermann et al. (2013) propose an option contract to derive the optimal booking policy for a system consisting of a freight forwarder and a cargo airline. They analyse the impact of overbooking on cargo airline’s profitability, and demonstrate the advantageous performance of the proposed contractual agreement over the existing one by applying industrial real data.

Other analytical research topics related to air cargo management include shipment integration and consolidation (Leung et al., 2009), network planning (Derigs et al., 2009), and loading planning (Li et al., 2009). For example, Leung et al. (2009) focus on identifying the optimal air cargo shipments integration and consolidation decisions. In the problem setting of Leung et al. (2009), a freight forwarder plans the execution of diverse shipments for his consumers, and each shipment is composed of a series of sequential activities. Besides, each activity should be operated by a number of processing units. The authors claim that cost reduction can be achieved if some activities could be consolidated. Therefore, Leung et al. (2009) aim to decide which activity should be operated by which processing unit with the objective of minimizing the overall costs. To solve the problem, a branch-and-bound algorithm is built with some heuristics. From the perspective of air cargo flight network planning, Derigs et al. (2009) construct a novel planning approach and build new solution algorithms for the top global cargo airlines. The authors insist that the network planning procedure for air cargo logistics is challenging because it involves different business units to identify market potentials and allocate airlines' resources simultaneously. In Derigs et al. (2009), three scheduling stages (i.e., flight selection, aircraft scheduling, and cargo routing) are solved in two integrated models, while the objective of the optimization problem is to maximize the profits of the cargo airlines. Besides, the authors test the applicability of the proposed models based on real-world collected instances. On the other hand, Li et al. (2009) examine the impact of air cargo loading strategies on the financial performances of airlines with limited containers. A novel neighbourhood search heuristic which relaxes the subset-disjoint constraint is proposed to improve the solution efficiency by Li et al. (2009).

2.2.2. Pricing Strategies for Cargo Airlines

Regarding the pricing problem, although the significance and challenges of this crucial decision for air freight carriers have been realized, only a few pieces of studies have explored this critical issue. First, Azadian and Murat (2018) study a group pricing problem for an air cargo company. The authors state that it is a common practice for the transportation industry to group several locations and price these services on a group basis. Therefore, they formulate an integrated model to simultaneously decide the optimal group service locations and the corresponding prices. Besides, the authors construct a mixed-integer nonlinear programming model for the integrated problem which is solved by algorithms based on decomposition approaches. Second, considering a service supply chain consisting of an air freight airline and freight forwarders who compete for uncertain demand, Tao et al. (2017) explore the option contracts between the agents, and derive the optimal prices for the airline and the optimal reservation strategies for freight forwarders to maximize their expected profits. A Stackelberg game is established to model the behaviours of the supply chain members, while numerical experiments and sensitivity analyses are conducted to generate managerial insights in Tao et al. (2017). Similar to the above two studies, Chapter 4 also explores the pricing problems for air cargo carriers. However, different from them, this study simultaneously incorporates the uncertainties from both demand and operating costs, and market competition into the decision framework. Accordingly, the impacts of these crucial factors on the equilibrium prices can be investigated, thus generating useful insights and implications. More importantly, this work considers the carriers' risk attitudes towards profit uncertainties, which is novel in the air cargo pricing literature.

2.3. Decisions with Risk Considerations

Risk analysis is one of the most crucial topics in operations management over the past decade (Ching et al., 2009; Du et al., 2018; Shang et al., 2017). For example, Shen et al. (2013) study the performance of markdown money policy in a fashion supply chain composed of a risk-averse manufacturer and a risk-neutral retailer. Besides, Choi (2016) examines the supply chain coordination issues with risk-sensitive retail buyers under both symmetric and asymmetric information settings. The author illustrates that the risk attitudes of decision makers significantly influence the achievability of prefer coordination for a supply chain. Similarly, Xie et al. (2018) explore the conditions to achieve supply chain coordination with the consideration of retailers' risk behaviours. In the model setting of Xie et al. (2018), retailers could be risk-neutral, risk-averse, or risk-take in a unified framework. Therefore, the significant impact of risk attitudes on decision making is demonstrated through comparing the various settings (Xie et al., 2018). Furthermore, Zhang et al. (2016) investigate the effects of risk-averse behaviour and capital constraint on the optimal price and ordering quantity decisions for a newsvendor supply chain. In addition, risk analysis has been widely applied in the areas like personnel assignment (Lazzerini & Pistolesi, 2018), cybersecurity protection (Qin et al., 2018), Bayesian network modelling (Yang et al., 2018), and contamination of food production facilities (Chang et al., 2017).

2.3.1. Risk Analysis for Air Cargo Logistics

In the air cargo industry, if uncertainties (like uncertain demand and cost) exist, the performance of airlines will be affected and their profitability becomes volatile (Chiu & Choi, 2016). Therefore, how to improve decision making under an uncertain environment to alleviate profit risks becomes a critical problem for freight airlines. However, this topic is scarcely studied in the existing literature. From the perspective of capacity allocation, Wada et al. (2017) explore the optimal strategy for freight airlines with risk considerations. The authors propose that there are two capacity reservation tactics in the air cargo transportation industry. The first is to reserve by allotment with fixed prices (which is based on long-term contracts), while the second is to reserve the remaining capacity which is not allocated to allotment agreements.

Although the available capacity becomes uncertain, the second reservation tactic enables decisions to be made near the departure date. Both risk-averse and risk-neutral attitudes of airlines are considered in the decision framework of Wada et al. (2017) using the Conditional Value-at-Risk (CVaR) approach. Besides, Sample Average Approximation approach is applied to test the models using real data in Wada et al. (2017). From the discussion above, it is obvious that more research is needed to improve the decision making for cargo airlines with risk behaviour considerations.

2.3.2. Pricing Strategies with Risk Considerations

Some research has integrated risk considerations into the pricing decision framework. For example, Zheng et al. (2017) study the optimal pricing decisions for liner shipping companies who compete for uncertain demand, and the risk-averse behaviour of one participant is modelled by the conditional value at risk approach. Conditions when the equilibrium prices will increase or decrease along with competition level are analysed in Zheng et al. (2017). Besides, Agrawal and Seshadri (2000a) explore the pricing and ordering decisions for a risk-averse newsvendor facing with uncertain demand. They show that the risk-averse attitude could either raise or lower the retail price in different model settings. Besides, Li et al. (2014a) study the impact of risk preference of a retailer on the optimal pricing decisions for a dual-channel supply chain. They show that when the retailer becomes more risk-averse, the equilibrium retail price will decline if the uncertain demand follows a uniform distribution. A similar study could be found in Liu et al. (2016). Furthermore, Li et al. (2014c) analytically explore how the risk attitude of a retailer could affect the optimal price and promised delivery time decisions.

2.4. Mean-Variance Theory for Risk Analysis with Air Logistics

Regarding risk analysis, one of the most commonly applied analytical approaches is the mean-variance (MV) theory. The MV theory was firstly introduced for portfolio optimization in financial engineering (Markowitz, 1959), and then is widely used in supply chain and logistics operations problems (Chiu et al., 2015; Chiu et al., 2018; Choi et al., 2018; Li et al., 2014b). For instance, Chiu et al. (2015) solve the supply chain coordination problem with several risk-averse retailers and a risk-neutral manufacturer based on the framework of the MV theory. The authors find that the risk parameters play a crucial role in determining the efficiency of coordination contracts. They also show that the manufacturer could manage the retailer profit variance through adjusting the risk indicators. This study follows this research stream on risk analysis to apply the MV theory to measure the risk aversion behaviours of air cargo carriers. Specifically, like the literature, an MV objective is proposed which maximizes the expected profit of the air cargo carrier minus the variance of profit to characterize the equilibrium risk-averse pricing strategies.

To facilitate this research, the application of mean-variance theory in air logistics operations is reviewed in this sub-chapter.[9] Specifically, the MV analysis of operations management problems in global supply chains associated with air logistics is focused. Air logistics are related to operations management in various perspectives. First of all, for air-logistics related operations, such as crew scheduling, pricing, airline coordination, etc., the MV theory can be used for the respective risk analysis. Second, for non-air-logistics related companies and organizations, they need air logistics to provide express delivery services to them. Thus, from demand management, and supply management perspectives, air logistics plays a critical role and the MV theory can be applied to conduct analysis.

[9] As a remark, most part of this section is summarized in Choi, T. M., Wen, X., Sun. X.T., & Chung, S.-H. (2019). The mean-variance approach for global supply chain risk analysis with air logistics in the blockchain technology era. *Transportation Research Part E: Logistics and Transportation Review*, 127, 178-191.

This sub-chapter on the review of the MV theory application is organized as follows. Section 2.4.1 explores the air-logistics specific operations. Then, Section 2.4.2 examines the demand management operations with the use of air. Next, Section 2.4.3 reviews the literature on supply management with the application of air transport. At last, the application issues for supply-demand coordination are discussed in Section 2.4.4.

2.4.1. Air Logistics Related Operations

This part reviews the literature in air logistics related operations from the perspective of strategic decision making, and discusses the risk analysis issues and applications of the MV theory in these areas.

Strategic decisions in air logistics management, such as service pricing, airline alliances and competitions, entry decisions, revenue management, capacity management, and booking control management, are crucial for the profitability and development of air cargo companies. For example, Wang et al. (2017) study the strategic upstream entry decisions for mainline air carriers in an air cargo service supply chain when the competition on promised delivery time is intensive. The value of vertical cooperation and upstream competition, equilibrium profits, and channel structures are investigated by Wang et al. (2017). Interestingly, the authors find that the upstream entries of mainline carriers could lead to either a win-win situation or a lose-lose situation for the mainline carrier and the incumbent regional carrier.

In the literature, Azadian and Murat (2018) point out that among all the strategic air logistics management problems, pricing strategy is the most important but challenging decision for freight airlines. Azadian and Murat (2018) focus on a group-to-group air logistics service pricing problem, and develop an integrated model to determine the optimal group service locations and the corresponding prices simultaneously. In their model, the price elasticity of consumer demand is considered, and computational experiments are conducted to show the effectiveness of the proposed model in Azadian and Murat (2018). Additionally, facing uncertain market demand, Tao et al. (2017) investigate the optimal prices for freight airlines to sell capacity to forwarders, as well as the optimal prices charged for the end consumers by forwarders. A Stackelberg game is established to model the behaviors of airlines and forwarders to maximize their expected profits. Besides, the authors also examine the efficiency of option contracts between cargo airlines and freight forwarders where the contract could be executed after the uncertain market demand is realized. However, despite the intrinsic diverse uncertainties in the air logistics mediated supply chains (e.g., demand, cost), in the above reviewed works, the profit risks or profit volatility have not been explored. Therefore, the MV theory can be applied to characterize the profit risks aversion objective function for airlines to improve their decision making.

2.4.2. Demand Management

Air logistics can help a lot for companies to deal with demand variation. For example, in securing supplies from vendors, companies employ air transportation to help reduce the delivery lead time and this relates to industrial practices such as quick response, emergency supply, responsive supply, etc. With a reduced lead time, the global supply chain becomes more responsive to market demand changes and the buyers can achieve better forecasting and improve its ordering decisions and inventory planning.

In the literature, this subject has been examined under the topic of quick response. For instance, Iyer and Bergen (1997) establish that in a supply chain, postponing the ordering decision under quick response can yield a higher benefit for the retailer but not for the manufacturer when the inventory service level is not very low. The authors propose measures to achieve Pareto improvement in the supply chain channel. Cachon and Swinney (2011) study the use of quick response in the fashion industry to build the fast fashion business model. The authors consider the presence of forward-looking strategic consumers and they propose the use of enhanced design as a part of the business strategy. Chen et al. (2016) study the use of multiple shipments which employ information benefits similar to what quick response achieves. The authors highlight the significance and application of the inventory subsidizing supply contract. Lin and Parlaktürk (2012) investigate quick response under a competitive market. They uncover that the findings towards quick response under competition are very different from the ones without competition. Yang et al. (2015) examine quick response with the consideration of forward-looking consumer behaviors. The authors also reveal how the structure of the supply chain would make a difference. Recently, Choi et al. (2018) study quick response supply chain systems in which the retailers possess a stochastic risk attitude. They discover the fact that it is unwise to ignore the stochastic risk attitude because it will lead to mistakes in supply contracting. In all of the above quick response programs, one way to achieve speedy response is to employ a quick delivery mode. For global supply chains, air transportation is the most reliable and speedy delivery mode which can help. In the above reviewed studies, they all focus on exploring quick response (which could relate to the use of air transportation) from the perspective of expected benefits. They do not explore the profit volatility or the profit risk. Recently, Choi (2018) extends the classic study by Iyer and Bergen (1997) and studies the quick response supply chain using the MV theory. The mechanism of using MV theory to model the risk-sensitive decision making for the buyer to achieve quick response is described as follows.

To be specific, here, an operations problem similar to Choi (2018) is considered: A buyer orders a newsvendor type of seasonal product from the supplier using a wholesale pricing contract. The unit wholesale price is w, the unit product revenue is p, and the product leftover carries a net unit value v. The order quantity is denoted by q. Define the scenario with the use of air shipping by AIR and the scenario without using air shipping by $\overline{AIR}$.

Using the normal distribution and formulating the problem using the Bayesian conjugate pair, the following could be obtained: Demand uncertainty at the time point when the buyer places the order without the use of air shipping, i.e. the slow delivery mode, is denoted by $\sigma_{\overline{AIR}}$. With air shipping, the buyer places the order at a time point closer to the selling season and the demand uncertainty is σ_{AIR}. By Bayesian theory, it is known that $\sigma_{AIR} < \sigma_{\overline{AIR}}$.

Under Scenario $l \in \{\overline{AIR}, AIR\}$, the respective expected profit and variance of profit are represented as follows: $EP_l(q)$ and $VP_l(q)$. Under the newsvendor problem setting, it is known that $EP_l(q)$ is concave and $VP_l(q)$ is monotonically increasing. The standard normal density function, the standard normal cumulative distribution function and the standard normal right linear loss function are represented as $\theta(a)$, $\Theta(a)$ and $\Psi(a)$, respectively. In particular,

$VP_l(q) = (p-v)^2 \sigma_l^2 \xi\left(\dfrac{q-\mu_l}{\sigma_l}\right)$, where $\xi(a) = a\theta(a) + (a^2+1)\Theta(a) - [\theta(a) + a\Theta(a)]^2$.

Under the MV theory, a risk aversion tolerance threshold $K_{Risk} \geq 0$ is defined and the following optimization problem for the buyer is formulated:

$$\max_q EP_l(q)$$
$$s.t.\ VP_l(q) \leq K_{Risk}, \quad l \in \{\overline{AIR}, AIR\}.$$

Note that the problem above is a classic mean-variance optimization problem. Solving it and getting the answer will yield the optimal ordering quantity under Scenario $l \in \{\overline{AIR}, AIR\}$.

2.4.3. Supply Management

Supply side can be stochastic and unreliable. Even if a situation when demand is perfectly known in advance is considered, if supply is uncertain and highly volatile, the global supply chain's efficiency is still under threat. For instance, supplier capacity, product yield, supply disruption, etc., are all important parameters which may be random. If the buyer can acquire better information regarding supply, it can do a better job in its operations management. Thus, air logistics play a role because the buyer can employ the air logistics to reduce lead time and grant itself more time to observe the supply side information and improve its decision making.

Now, some studies related to supply side uncertainty are reviewed. Altug and Muharremoglu (2011) explore the early supply information for the buyer. They theoretically derive the value of supply side information which consists of operations downtime and inspection time. Atasoy et al. (2012) explore the case in which the supplier can forecast the supplier's inventory situation. The authors study how advance supply information can be used to reduce supply uncertainty. Çınar and Güllü (2012) examine the advance capacity information for a buyer in a supply chain with flexible production capacity. The authors highlight that the use of advance capacity information is especially effective if the supplier's capacity has a high level of volatility. Dettenbach and Thonemann (2015) study the value of supplier's yield information. The authors focus on uncovering how supply side yield information can be used to improve inventory planning and reduce costs. Luo and Chen (2017) examine the supply chain system with random yields from supply side. The authors consider the case when demand is fixed. They demonstrate how the option contract can be set in a way which achieves coordination in the supply chain for both the manufacturer's purchasing quantity and the supplier's production quantity. Gao et al. (2017) investigate how the early supply signal can be used to improve supply chain operations. The authors develop a mechanism for the buyer to consider when it is wise to acquire supply information. Li (2017) explores the optimal purchasing policy in the presence of random yield suppliers. The author considers the presence of a manufacturer with a fixed demand, who needs to place orders and get supplies from two suppliers. Yields of suppliers are uncertain which create challenges. Note that in the above reviewed studies, supply information is treated as a critical treasure and supply information updating helps to improve operations performance. One way to allow the buyer to observe the supply side is to employ air shipping so that lead time is reduced. In this case, the buyer can spend more time to observe the situation of the supplier and make a wiser decision. In terms of profit risk, none of the above reviewed studies have considered profit uncertainty and the implied risk.

Thus, similar to demand management, the MV theory can also be applied to conduct risk analysis for the global supply chains with supply side uncertainty. For example, a global supply chain in which a single buyer needs to order from a supplier is considered. The supplier is unreliable and hence may not fulfill all the ordered quantity. The specific allocation of inventory (e.g., granting 60%, 70%, 80%, 90%, etc., of the ordered quantity to the buyer) depends on the level of shortage at the supplier side. In this situation, if the buyer chooses the slow mode of delivery, it will have to order earlier, and it has poorer knowledge regarding the supply's situation in the shortage level. If the buyer can choose the quick delivery mode using air shipping, it will be able to learn and get more up-to-date information regarding the shortage level in supply and then make the optimal decision. In terms of modeling analysis, a similar MV optimization problem as shown in Section 2.4.2 can also be constructed.

2.4.4. Supply-Demand Coordination

In general, both demand and supply sides can be associated with uncertainties and hence risks are present. To achieve supply-demand coordination with respect to the presence of dual-uncertainty is an uneasy task as it means there exist multiple sources of uncertainties (Choi et al. 2017).

To be specific, by shortening lead time, the buyer is benefited with respect to the management to both demand and supply sides. For example, for the demand side, the quick response program can be implemented. For the supply side, air logistics is known to be stable and hence it can reduce supply lead time uncertainty. The buyer can also observe and acquire more information regarding the supply side situation.

In the literature, studies exploring both supply and demand uncertainties have appeared in recent years. Some of them are reviewed as follows.

Chen and Xiao (2015) study outsourcing strategies with demand and supply uncertainties. The authors also explore the impact brought by channel leadership. They uncover that the manufacturer does not want to go outsourcing when the risk of disruption is low and the available production capacity is sufficient. They also interestingly find that if the risk of disruption is very high, the manufacturer will go outsourcing irrespective of the availability of production capacity. Jabbarzadeh et al. (2016) explore global supply chains with disruptions from supply and demand. They establish a stochastic optimization model and conduct computational studies. The authors discover how demand volatility and supply uncertainty (in terms of capacity) affect the optimal decisions. Negahban and Smith (2016) investigate how demand and supply uncertainties affect new product development. The authors highlight the importance of taking both demand and supply uncertainties into considerations. By conducting Monte Carlo simulation experiments, the authors show that when risks are included in the decision-making problem, the optimal decision would be very different. Jabbarzadeh et al. (2017) study supply and demand uncertainties by exploring a production–distribution control problem. The authors illustrate the application of their proposed method via conducting extensive computational studies.

In terms of analytical modelling, as an example, one can simply combine the demand management and supply management models that are proposed in previous sections. Of course, when both sources of uncertainties as well as the impact of using air shipping mode are considered, one may come across the situation that for the derivation of the variance of profit function, there are two sources of uncertainties. As a result, it is necessary to employ the following formula for the correct estimation of the unconditional variance of profit: $V(P) = E_X[V_{Y/X}(P)] + V_X[E_{Y/X}(P)]$. In words, if P denotes profit, the unconditional variance of profit is the sum of "expected conditional variance of profit" and "variance of conditional expected profit".

2.5. Summary

From the above literature review, the following crucial research gaps regarding air logistics operations can be summarized.

From the perspective of air passenger logistics, it is obvious that cabin crews are studied much less than cockpit crews in the CPP literature. This is mainly caused by the larger problem scale and complexity of the cabin crew pairing problems, and the relatively higher importance of cockpit crews for the operations of aircrafts. However, the significance of cabin crews is also realized, and the associated managerial decisions are also crucial for the performance of flights and the profitability of airlines. The detailed research gaps are listed as follows.

First, most of the existing cabin CPP research treats cabin crews as identical as cockpit crews. That is, cabin crews are assumed to fly a single aircraft type and modelled as teams without considering the multiple classes. However, in practice (e.g., The Airways), cabin crews are cross-qualified to fly mixed types of aircraft, and they are scheduled based on their classes. Besides, the team modelling approach fails to characterize the heterogeneous requirements for multi-class cabin crews of different flights. Accordingly, the team modelling approach can lead to low manpower utilization because the actual cabin crews required by a team must satisfy the maximum requirements among all the flights in that team pairing. However, on the other flights with fewer requirements, some of the manpower assigned is not used. Although working as teams is helpful for employees' psychological health, this thesis research focuses on highlighting the impact of individual modelling approach on airlines' cost reduction and manpower utilization improvement, which provides useful guidelines for airlines in decision making.

Second, there is no literature integrating the availability constraint for each class of cabin crews into the CPP. As discussed, the crew scheduling problem is divided into two sequential problems of a CPP and a CAP. Without considering the crew availability constraint in the CPP, additional proceedings (e.g., pairing breaking & reconstruction) which causes undesirable increased operating costs could be induced in the stage of crew assignment problem. Although some previous studies have proposed to impose an upper limit on the manpower used in the stage of CPP (in teams), the related study of this thesis research is different from them because the availability constraint for each individual class of cabin crews is considered.

Third, the airline practical operation of CCS is rather underexplored in the literature. As mentioned, CCS is essentially a practical strategy to deal with the cabin crew shortage problem caused by the variations in manpower requirement during flight fluctuation. Observing this real-world practice and the importance of this strategy on airline operations, it is significant and worthwhile to investigate the impact of CCS on cabin crew management.

Fourth, to the best of our knowledge, no prior study analyzes the impacts of the relationship between cabin crew availability with manpower requirement benchmarks on cabin crew management in the literature. However, the analysis in this study shows this relationship is critical to determine the cabin crew planning strategies to be adopted.

In conclusion, the research on the cabin CPP is rather inadequate, and the pairing generation methodology for cabin crews still has a large room for improvement. The literature will benefit from bridging these gaps to mitigate the deficiencies of the existing methodologies. Accordingly, this study has proposed a novel individual cabin crew pairing approach which considers the distinctive characteristics of cabin crews (as presented in Chapter 3).

On the other hand, from the perspective of air cargo logistics, it is clear that relatively limited research has studied the pricing decisions for air cargo carriers. Besides, none of the current studies has investigated the integrated impact of market competition, demand uncertainty and cost uncertainty on the optimal prices. More importantly, to be best of our knowledge, no previous research has explored how risk behaviors of decision makers affect the equilibrium pricing decisions for the air cargo logistics industry. Therefore, one of the objectives of this thesis is to bridge these significant literature gaps by conducting risk analysis for cargo airlines' pricing strategies, which is described in Chapter 4. This work differs from other studies and becomes the first research that explores the pricing problem for competing risk-averse air cargo carriers facing uncertain demand and costs.

Chapter 3. A Novel Pairing Approach for Cabin Crews

Realizing the research gaps in the cabin crew pairing literature and the real problems revealed from the air passenger logistics operations management (from Chapter 2), this chapter proposes a novel pairing generation methodology for multi-class cabin crews, which is proven to significantly improve cabin crew utilization and reduce associated costs (named as *Multi-class individual cabin crew pairing problem with availability and controlled crew substitution* (MICCPP-ACCS)), solved by a branch-and-price exact method which combines column generation and branch-and-bound[10]. With the consideration of flight requirement heterogeneity, the proposed pairing generation methodology incorporates the cross-qualification and availability constraints for multi-class cabin crews into the model. Rather than modelling teams as in the most existing literature, this work formulates each cabin crew individually in accordance with the emerging airline practice. Besides, the strategy of CCS is embedded to hedge against cabin crew requirement variation and manpower shortage during flight fluctuation. Compared with the literature, the proposed methodology distinguishes itself from others by its unique characterization of cabin crews and the effect of CCS on the cabin CPP, which underlies the modelling and analysis of this work. Furthermore, the crew substitution modelled in this work (CCS) exhibits the following specific features: i) the cabin crew availability constraint for each class is considered; ii) the crew substitution in this work could be controlled to ensure that at least one qualified cabin crew is assigned to each flight and no unnecessary substitution is allowed; iii) extra cabin crew variables are introduced to ensure solution feasibility. Besides, it should be pointed out that the planning horizon of the cabin CPP studied here is one week, while the "manpower availability" considered in this work refers to the maximum number of

[10] As a remark, most part of this chapter is summarized in Wen, X., Chung, S.-H., Ji, P., Sheu, J.-B. & Choi, T. M. (2019). Multi-Class Cabin Crew Pairing Problems with Controlled Crew Substitution in Airline Operations. *Transportation Research Part B: Methodological*, under the second round review.

pairings that can be generated for the planning horizon in the cabin CPP (similar to the literature like Graves et al. (1993)). Note that this study is not aiming at considering the precise availability for each specific cabin crew every day by building a CPP&CAP fully-integrated model. Instead, this research focuses on demonstrating the importance of scheduling cabin crews individually and considering the entire flight schedule rather than decomposing it by aircraft types, and showing the advantages of the controlled crew substitution strategy based on the crew pairing framework. Therefore, the number of individual pairings used is applied to approximate the number of cabin crews required for a week at the stage of CPP, instead of considering the precise manpower availability each day. Accordingly, this study proposes to impose an upper limit on the individual pairings derived to alleviate the shortcomings of the rigid separated scheduling approach to some extent, and to show the crucial impact of such an upper limit on the solutions. Apart from the primary methodology MICCPP-ACCS, a *Multi-class individual cabin crew pairing problem with availability* (MICCPP-A) which is a simplified version of MICCPP-ACCS without the function of CCS is constructed, to derive more managerial insights regarding airline cabin crew resource management.

This chapter is structured as follows. First of all, Section 3.1 provides problem statement which consists of definition (Section 3.1.1), duty-based flight network construction (Section 3.1.2), flight requirement heterogeneity (Section 3.1.3), and the strategy of controlled crew substitution (Section 3.1.4). Then, the mathematical models are developed in Section 3.2, in which the traditional crew pairing model (TCCPP), the proposed individual pairing model with controlled crew substitution (MICCPP-ACCS), and the simplified individual pairing model without controlled crew substitution (MICCPP-A) are constructed sequentially in Section 3.2.1, Section 3.2.2, and Section 3.2.3. Next, Section 3.3 presents diverse crucial manpower availability-requirement relationships and their managerial insights regarding cabin crew management, followed by the solution approach development stated in Section 3.4. Finally, real-world collected flight schedule based computational experiments are shown in Section 3.5 to demonstrate the merits of the proposed models.

3.1. Problem Statement

This sub-chapter details the distinctive characteristics of the multi-class cabin CPP arising from the airline practice, which underlines the differences between this work with the literature. First, the definitions regarding the cabin CPP are introduced. Then, the duty-based networks are constructed according to the collective rules and regulations. Third, the impact of flight heterogeneity in terms of cabin crew requirement is demonstrated. Lastly, the principles and mechanisms of CCS are introduced. The notations used in this work are summarized in **Table A-1** in Appendix A.

3.1.1. Definitions

The analysis in this part of the thesis employs the aviation terminologies from Belobaba et al. (2015) and The Airways and The Avoidance of Fatigue in Aircrews (CAD 371) published by the Civil Aviation Department of the Government of the Hong Kong Special Administrative Region. Given a flight schedule containing the information regarding flight departure / arrival airports, flight departure /arrival times, types of aircraft with unique cabin crew requirements, the cabin CPP aims to determine sufficient legal pairings to cover all flights' requirements for each class with the minimum cost, while satisfying all the regulations imposed by labor unions, civil aviation departments, and airlines. A duty is composed of a sequence of flights separated by transits, coupled with a briefing period at the start and a debriefing at the end. A duty period refers to the elapsed time from the start of the duty to the end of the duty. A rest is a continuous time period between two consecutive duties, during which cabin crews are free of any duty. A legal pairing is a sequence of duties connected by rests, operated by the same cabin crew, which starts and ends at the home base, and satisfies diverse regulations such as maximum elapsed time and maximum number of flights. The total elapsed time of a pairing is known as the time away from base (TAFB) in the literature (Gao et al., 2009). In some cases, cabin crews are placed on a scheduled flight as passengers for repositioning to an airport where they are required to operate duties. This type of flights is called deadhead (Yan & Chang, 2002). A typical pairing generally lasts for two to five days (Cordeau et al., 2001), while a cabin crew commonly flies four to five pairings in a month (Anbil et al., 1992). The TAFB is applied to represent the pairing cost in this study. In the following, the pairings for individual cabin crews considered in the current work are called as individual pairings, while those for cabin crew teams in the literature as team pairings. A cabin crew team consists of certain quantities of cabin crews of each class who stay together throughout the team pairing.

3.1.2. Duty-based Networks

In this part, flight networks for pairing generation are built, where the planning horizon is a week. In the literature, two types of flight network have been developed: Flight-based network and duty-based network. In both networks, a source node and a sink node are used to represent the home base for cabin crews. However, the two types of network are different in terms of intermediate nodes and arcs. In a flight-based network, each intermediate node stands for a flight, while arcs perform as the connections between flights. The source node connects every flight that departs from the home base, while each flight arriving at the home base is connected with the sink node. On the other hand, in a duty-based network, intermediate nodes represent duties, while arcs stand for the connections between duties. Here, the source node connects every duty that departs from the home base, while each duty arriving at the home base is connected with the sink node. In order to build a duty-based network, flights are firstly connected to form duties according to the duty-related regulations imposed by authorities and airlines (e.g., maximum number of flights per duty). Therefore, the duty-based network is widely applied in the literature due to the enhanced optimization efficiency because some regulations are already considered during the network construction process (Vance et al., 1997a). Hence, this work utilizes the duty-based network.

Rules and regulations. To ensure the safety level of flights and reduce the fatigue level of cabin crews, governmental authorities, labor union, and airlines have prescribed many rigid regulations on cabin crews, which influences the development of duties and pairings. This study considers the following rules based on the practical operations of CAD 371. Firstly, two consecutive flights could be connected and operated by the same cabin crew only when the arrival airport of the first flight is the departure airport of the second flight, with a minimum 75 minutes and a maximum 240 minutes of transit time between these two flights. Secondly, the briefing period before a duty lasts 60 minutes while the debriefing period after a duty lasts 30 minutes, with a maximum of three flights in a duty. Regarding the longest length of a duty period, it varies according to the local starting time and the number of flights of the duty, as explained in **Table 3-1**. For example, if a duty starts at 07:30 in local time with two flight legs, the longest duty period is then 12.25 hours. Thirdly, regarding the connection of two duties to be flew by the same cabin crew, the arrival airport of the first duty should be the departure airport of the second duty. Besides, there should be a rest period lasting from 720 minutes to 2160 minutes between the two duties if the former duty lasts no more than 12 hours; otherwise, a minimum of 840 minutes of rest should be assigned to the cabin crew. Lastly, maximum 5 duties, maximum 12 flights, and maximum 7200 minutes of TAFB are allowed for a pairing. It should be pointed out that the rules and regulations for cabin crews are identical for the pairing models proposed in this work.

Table 3-1. Maximum duty periods (in hours).

Local starting time	No. of flight legs		
	1	2	3
07:00-07:59	13	12.25	11.5
08:00-12:59	14	13.25	12.5
13:00-17:59	13	12.25	11.5
18:00-21:59	12	11.25	10.5
22:00-06:59	11	10.25	9.5

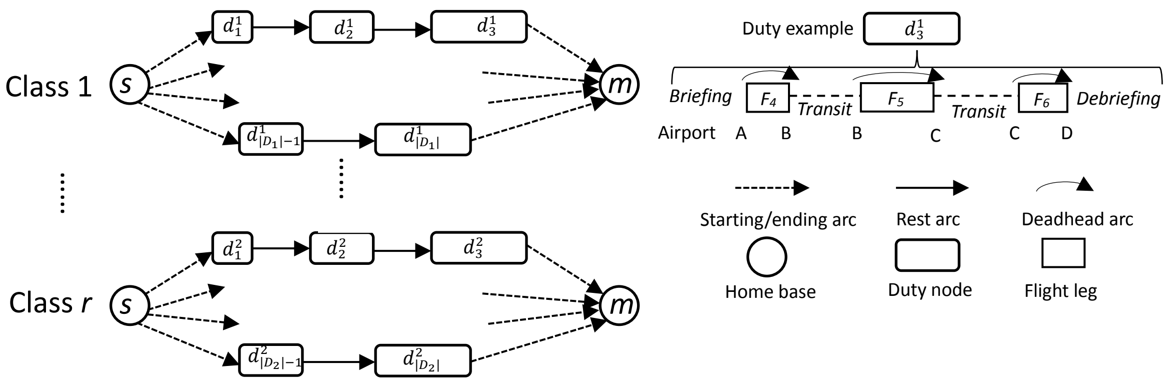

Figure 3-1. Typical duty-based networks for multi-class cabin crews.

Network construction. Based on the regulations described above, the acyclic duty-based networks $G^r = (N_r, A_r)$ for each class ($r \in R$) of cabin crews (an example is depicted in **Figure 3-1**) are constructed. Note that all possible duties are built for the network development according to the rules and regulations. Specifically, N_r is the set of nodes, denoted by n_r, while A_r is the set of arcs, denoted by $arc_{(n_r, n_r')}$. Note that the networks for each class are identical since the working rules are the same. Therefore, it is only necessary to develop the network for one class, which then is applicable to others. First of all, flights ($i \in F$) are connected to form duty nodes ($d_k^r \in D_r$) through transits according to the first and second sets of rules mentioned above. Note that one flight could appear in more than one duty (because a flight could be connected with different flights to form different duties). $F_{d_k^r}$ represents the set of flights contained in the duty node d_k^r. A typical duty is illustrated in the upper right corner of **Figure 3-1**, where duty d_3^1 is composed of $F_{d_3^1}$ (Flights 4, 5, and 6). Deadhead arcs are parallel to flights. Then, the constructed duty nodes are linked by rest arcs (i.e., $arc_{(d_{k_1}^r, d_{k_2}^r)}$) with respect to the third set of regulations. All duties starting from the home base are connected with the source node (s) through starting arcs (i.e., $arc_{(s, d_k^r)}$), while those ending at the home base are linked with the sink node (m) through ending arcs (i.e., $arc_{(d_k^r, m)}$). Both s and m represent the home base, while $SA_r, EA_r$and RA_r are the sets of starting, ending, and rest arcs respectively. After the construction of duty nodes and arcs, the duty-based network G^r for Class r cabin crews is obtained. Specifically, the node set N_r contains the source/sink nodes together with all the built duty nodes ($N_r = D_r \cup \{s, m\}$), while the arc set A_r is composed of all the starting/ending arcs together with the developed rest arcs ($A_r = SA_r \cup EA_r \cup RA_r$). For each individual Class r cabin crew, a s-m path in G^r corresponds to a potential individual pairing. All feasible individual pairings are contained in the networks. However, not all s-m paths in G^r are feasible individual pairings due to the violation of pairing related regulations (the last set of rules) which are usually called *resources* ($\tau \in \Theta$) in the literature. A legal individual pairing (path), for example, $s \rightarrow d_1^1 \rightarrow d_2^1 \rightarrow d_3^1 \rightarrow m$, which respects all the resources of maximum number of duties, number of flights, and TAFB, is denoted by $j_r \in J_r$, where J_r is the set of all feasible Class r individual pairings (paths). Selecting an individual pairing for a cabin crew means that all the flights contained will be operated by the corresponding staff. As each flight i requires a varying quantity of cabin crews for Class r (b_i^r), the corresponding number of individual pairings of Class r that contains flight i should be selected in the solution to facilitate the normal operations of the flight.

3.1.3. Flight Requirement Heterogeneity

This part discusses the impact of flight requirement heterogeneity and the deficiency of the traditional modelling approach of treating cabin crews as teams in the most existing literature.

An example based on Class 1 is illustrated in **Figure 3-2**, in which three flights, Flights 7, 8, and 9 (i.e., F7, F8, and F9), are covered by three pairings. Specifically, path 1 contains d_4^1 (Flights 7 and 9), while path 2 covers d_5^1 (Flight 8). Besides, Flights 8 and 9 (d_6^1) are included in path 3. The three flights have heterogeneous manpower requirements. Specifically, Flights 7 and 8 demand only one ($b_7^1 = b_8^1 = 1$), while Flight 9 needs two ($b_9^1 = 2$) Class 1 cabin crews. It is assumed that all the remaining flights on these pairings (not shown in **Figure 3-2**) require only one Class 1 cabin crew.

Two scenarios, one modelling cabin crews as teams while the other modelling individually, are compared to show the deficiencies of the traditional team modelling approach. In the first (team) scenario, the teams corresponding to team pairings 1 and 3 should be equipped with two Class 1 cabin crews because Flight 9 needs two, although Flights 7 and 8 only require one. Therefore, for these two team pairings, one staff will be redundant on Flights 7 and 8, respectively. Besides, the team pairing 2 needs one Class 1 cabin crew. To cover all flights' requirements, the team pairings 1 and 2, or 1 and 3 should be selected. Consequently, regarding these two solutions, a minimum of three Class 1 cabin crews are demanded to cover all three flights (two for team pairing 1 and one for team pairing 2), with a manpower waste on Flight 7. In the second (individual) scenario, cabin crews serve flights individually with the flexibility to operate any feasible flights without the restriction of teams. In this example, only two Class 1 cabin crews, one for individual pairing 1 and another for individual pairing 3, are needed to satisfy all the flight requirements, without any manpower waste. Consequently, it is shown that modelling cabin crews as teams working together throughout the pairing will lead to low cabin crew flexibility and utilization when the flights requirements are heterogeneous. This is because the actual cabin crews required by a team must satisfy the maximum requirements among all the flights in the team pairing. However, on the other flights with fewer requirements, some of the manpower assigned becomes redundant. Differently, modelling cabin crews individually can avoid the deficiencies of the traditional team modelling approach and lead to an improvement in manpower flexibility, which further enhances cabin crew utilization. Actually, some airlines and companies nowadays are providing optimization software which deals with the flight requirement heterogeneity problem for airlines. To be specific, the optimization software uses many copies of a flight, each of which represents a person (or group of persons) needed. Then, it builds pairings to cover these flight copies, which are further covered by monthly schedules. However, this industrial optimization approach is in advance of academic publications, which has been scarcely studied. On the other hand, in the literature, the team-based pairing approach still occupies the main research stream. Therefore, this work utilizes the team-based pairing approach as a benchmark to demonstrate the importance of modelling cabin crews individually and the advantages of the proposed models.

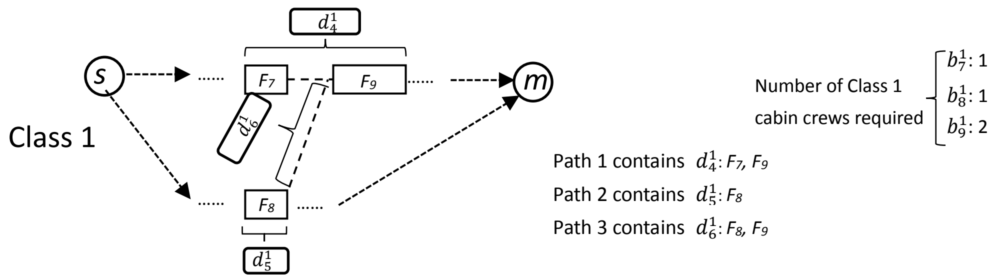

Figure 3-2. An example of flight manpower requirement heterogeneity based on Class 1.

3.1.4. Controlled Crew Substitution

With finite availability, there might be insufficient cabin crews to cover all the flights scheduled during the manpower requirement variation led by flight fluctuation. Cabin crew shortage (insufficiency) refers to a situation where the available Class r cabin crews cannot fulfill all flight requirements on their own. To deal with the manpower shortage problem, The Airways, apply the strategy of CCS, to utilize cabin crews from other classes (*substituter*) to substitute the originally required ones (*substitutee*), to derive feasible solutions[11], and reduce the impact of manpower shortage. It should be emphasized that crew substitution can be applied only when some classes of cabin crew are in a shortage. If all classes of cabin crew are sufficient, no substitution is allowed. That is, crew substitution is under control for the purpose of facilitating normal flight operations, instead of saving costs. Arranging cabin crews individually facilitates the implementation of CCS by allowing them to fly any feasible flights with high flexibility, instead of being bundled with teams. The impact of flight fluctuation on airline manpower management is significantly reduced by CCS through the improvement of cabin crew utilization. With this strategy, the normal operations of a flight are not disrupted, by assigning sufficient cabin crews of all classes that is no less than the total requirements of the flight, no matter which specific classes are insufficient.

[11] Note that short-haul and long-haul flights are always scheduled separately in airlines practice. Therefore, it rarely happens that a short-haul cabin crew is assigned with a substitution job on a long-haul flight.

This condition is called the *total satisfaction constraint*. The number of Class r cabin crews assigned to flight i is denoted as q_i^r, and the number of Class r cabin crews required by flight i as b_i^r. Therefore, the total satisfaction constraint is translated into Eqs. (3-1), where the right-hand side $\sum_{r\in R} b_i^r$ is the total number of cabin crews of all classes required by flight i. Note that according to the practice of The Airways, all classes of cabin crews can be substituted by other classes when they are in a shortage.

$$\sum_{r\in R} q_i^r \geq \sum_{r\in R} b_i^r, \qquad \forall i \in F. \qquad \text{Eqs. (3-1)}$$

On the other hand, The Airways also regulate that at least one qualified cabin crew from the required class should be assigned to each flight (called the *minimum satisfaction constraint*), as in Eqs. (3-2).

$$q_i^r \geq 1, \qquad \forall i \in F,\ \forall r \in R. \qquad \text{Eqs. (3-2)}$$

A simple example of CCS is illustrated in **Figure 3-3**. The example considers Flight 10 with manpower requirements for Class 1 and 2 cabin crews. To be specific, Flight 10 demands two Class 1 cabin crews ($b_{10}^1 = 2$) and one Class 2 cabin crew ($b_{10}^2 = 1$). Regarding manpower availability, it is assumed that Class 1 has one cabin crew available, while Class 2 has two. Therefore, a shortage of Class 1 happens, while a Class 2 cabin crew flies a deadhead arc on Flight 10. With the application of CCS, the deadhead Class 2 cabin crew on Flight 10 (substituter) could be a temporal Class 1 member (substitutee), to prevent Flight 10 from operation disruptions due to manpower shortage. On the other hand, if substitution is not applied, one extra Class 1 cabin crew should be employed to satisfy the requirement of Flight 10, causing extra costs. From this point, the application of CCS could not only facilitate normal flight operations, but also help reduce costs.

In conclusion, CCS is essentially a methodology to deal with the manpower shortage dilemma during manpower demand variation through cabin crew utilization improvement, which helps maintain normal flight operations and relieve the influence of flight fluctuation. Furthermore, it should be pointed out that the manpower substitution can be applied only when certain classes are insufficient. Unnecessary substitutions must be avoided when the cabin crew availability of each class is adequate to operate all flights.

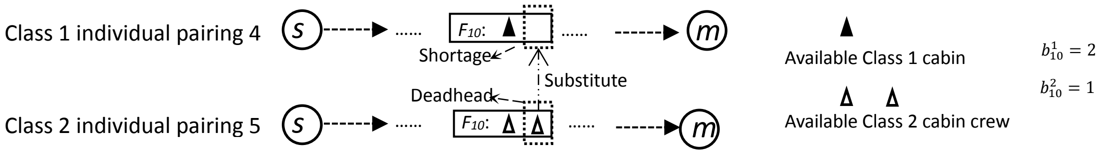

Figure 3-3. A simple example of CCS.

3.2. Model Development

In this sub-chapter, the traditional models in the literature are first reviewed. Next, the proposed MICCPP-ACCS model is formulated, followed by the simplified version MICCPP-A.

3.2.1. The Traditional Model

In the most existing literature, the cabin CPP is solved in each separate aircraft type while the flight requirements are assumed to be homogeneous (e.g., Erdoğan et al., 2015, Weide et al., 2010). The traditional cabin CPP is denoted as TCCPP hereafter, and is modeled as follows. Note that the index *t* is used to represent cabin crew teams for each separate aircraft type, while j_t is applied to stand for the team pairing for cabin crews. The binary decision variable x_{j_t} is for cabin crew teams, representing whether the team pairing $j_t \in J_t$ is selected or not. Besides, the binary flight coverage coefficient a_{ij_t} represents whether the team pairing j_t covers flight i. The cost of a team pairing c_{j_t} is represented by the TAFB of j_t.

(TCCPP)	Min	$\sum_{j_t \in J_t} c_{j_t} x_{j_t}$		Eq. (3-3)
	s.t.	$\sum_{j_t \in J_t} a_{ij_t} x_{j_t} \geq 1,$	$\forall i \in F,$	Eqs. (3-4)
		$x_{j_t} = 0 \text{ or } 1,$	$\forall j_t \in J_t.$	Eqs. (3-5)

The objective Eq. (3-3) is to determine a subset of cabin crew team pairings from the entire team pairing pool with a minimum (pairing) cost, subject to a set of flight coverage constraints Eqs. (3-4), requiring that each flight is covered by at least one team. Besides, following the main stream of the CPP literature (e.g., Erdoğan et al., 02015), the manpower availability limitation is not considered in TCCPP. As TCCPP fails to recognize the multiple classes of cabin crews, only one duty-based network is needed for the generation of team pairings.

Although the complexity of the cabin CPP can be significantly reduced by TCCPP, this scheduling approach is inconsistent with airline practice. Moreover, due to the decomposition by aircraft types, TCCPP fails to find the global optimal solution over the whole flight schedule involving various types of aircraft. More importantly, the flexibility and utilization of cabin crews are greatly impaired.

3.2.2. The Proposed MICCPP-ACCS

This part presents the mathematical model of the proposed novel pairing generation methodology MICCPP-ACCS. Given a flight schedule containing mixed aircraft types with heterogeneous cabin crew requirements, the mechanism of MICCPP-ACCS is to select a least-cost set of individual cabin crew pairings of each class from the entire individual pairing family, to satisfy the varying requirements of each flight with the assistance of CCS and a restriction on cabin crew availability. Herein, different from TCCPP, cabin crews are classified into different classes and modelled individually, rather than teams, through which the heterogeneous flights could be differentiated, and their specific manpower requirements could be considered. Moreover, the problem is not decomposed by aircraft types and cabin crews could fly any flights in the schedule in accordance with airline practice. The proposed MICCPP-ACCS is formulated in Eq. (3-6) to Eqs. (3-13). Specifically, x_{j_r} is the non-negative integer decision variable for individual pairing j_r for class r available cabin crew, while $x_{j_r^e}$ is for individual pairing j_r^e for class r extra cabin crew. μ is used to represent the unit substitution penalty cost, and *M* stands for the unit big penalty cost for extra manpower employment. Besides, the substitution recording variable s_i^r records the number of times of class r cabin crews being substituted by other classes on flight i. Similar to TCCPP, the binary flight coverage coefficient a_{ij_r} and $a_{ij_r^e}$ are applied for class r available and extra cabin crews, respectively. In addition, d_r represents the number of Class r available cabin crews.

Min	$\sum_{r\in R}\sum_{j_r\in J_r} c_{j_r}x_{j_r} + \sum_{r\in R}\sum_{i\in F}\mu s_i^r + \sum_{r\in R}\sum_{j_r^e\in J_r^e}(c_{j_r^e}+M)x_{j_r^e}$		Eq. (3-6)
s.t.	$\sum_{r\in R}\sum_{j_r\in J_r} a_{ij_r}x_{j_r} + \sum_{r\in R}\sum_{j_r^e\in J_r^e} a_{ij_r^e}x_{j_r^e} \geq \sum_{r\in R} b_i^r,$	$\forall i\in F,$	Eqs. (3-7)
	$\sum_{j_r\in J_r} a_{ij_r}x_{j_r} + \sum_{j_r^e\in J_r^e} a_{ij_r^e}x_{j_r^e} \geq 1,$	$\forall i\in F, \forall r\in R,$	Eqs. (3-8)
	$\sum_{j_r\in J_r} a_{ij_r}x_{j_r} + \sum_{j_r^e\in J_r^e} a_{ij_r^e}x_{j_r^e} + s_i^r \geq b_i^r,$	$\forall i\in F, \forall r\in R,$	Eqs. (3-9)
	$\sum_{j_r\in J_r} x_{j_r} \leq d_r,$	$\forall r\in R,$	Eqs. (3-10)
	$x_{j_r} =$ non-negative integer,	$\forall r\in R, \forall j_r\in J_r,$	Eqs. (3-11)
	$x_{j_r^e} =$ non-negative integer,	$\forall r\in R, \forall j_r^e\in J_r^e,$	Eqs. (3-12)
	$s_i^r =$ non-negative integer,	$\forall i\in F, \forall r\in R.$	Eqs. (3-13)

In MICCPP-ACCS, the available cabin crews are always the first resource to be selected to satisfy the flights scheduled. Instead of just taking binary values, the value of non-negative decision variable x_{j_r} represents how many times the individual pairing j_r is selected for class r available cabin crew. Once any class encounters a manpower shortage during flight fluctuation, CCS will identify the cabin crews of other classes to fill the vacancy with a substitution penalty cost μ. Additionally, the extra cabin crew variables $x_{j_r^e}$ with a big penalty cost *M* are introduced, to ensure solution feasibility in case the flights cannot be completely covered even with CCS. In practice, airlines can always employ temporary cabin crews and part-time cabin crews as extra manpower. Besides, as The Airways' pairing-related payment mechanism is based on the time length of pairings, in this work, TAFB is used to represent the pairing cost of (available and extra) cabin crew individual pairings (i.e., c_{j_r} and $c_{j_r^e}$). Note that both available and extra cabin crews are paid a fixed payment for a week (c_{fa} and c_{fe}, respectively, where $c_{fe} > c_{fa}$) by The Airways that should be considered in the overall cost analysis, but not affecting the MICCPP-ACCS objective value. Accordingly, the fixed payment cost is ignored during the model development, but shall be considered in the overall cost analysis in the Computational Experiments section (Total cost =

TAFB pairing cost + Available manpower fixed cost + Extra manpower fixed cost).

The minimization objective function Eq. (3-6) is characterized by three parts: i) Sum of the costs of available cabin crew individual pairings selected; ii) total substitution penalty costs across all flights and classes; ii) sum of the costs of extra cabin crews introduced. Specifically, the cost of an extra cabin crew further consists of the corresponding individual pairing cost $c_{j_r^e}$ and a big penalty value M[12]. Note that in MICCPP-ACCS, the substitution penalty cost μ is much larger than the general individual pairing cost, but much smaller than the big penalty cost M induced by the generation of an extra cabin crew individual pairing (that is, $c_{j_r}, c_{j_r^e} \ll \mu \ll M$). The constraints are classified into four groups – Eqs. (3-7) as group 1, Eqs. (3-8) and Eqs. (3-9) as group 2, Eqs. (3-10) as group 3, and Eqs. (3-11) to (3-13) as group 4.

The first group (Eqs. (3-7)) concerns flight coverage and crew substitution, which is equivalent to Eqs. (3-1). Specifically, the right-hand side of each row in Eqs. (3-7) specifies the total manpower demand across all classes of each flight to be scheduled (that is, $\sum_{r\in R} b_i^r$). The left-hand side represents the total number of cabin crews across all classes assigned to each flight (that is, $\sum_{r\in R} q_i^r$ in Eqs. (3-1)). Therefore, Eqs. (3-7) ensure that for each flight scheduled, the number of total cabin crews of all classes assigned is no less than the number of total manpower demand. In other words, Eqs. (3-7) facilitate the function of CCS, allowing cabin crews to substitute colleagues of other classes to ensure that all flights are completely covered. It is noteworthy that the cabin crews assigned to each flight could be either the available ones (x_{j_r}) or extra ones ($x_{j_r^e}$). However, the big M added into the objective function ensures that the least extra cabin crews will be selected.

Then, the cabin crew substitution proposed in Eqs. (3-7) is controlled by the second group of constraints. Firstly, Eqs. (3-8) represent the minimum satisfaction constraint (as discussed in Section 3.1.4, Eqs. (3-2)), to allocate at least one qualified

[12] For the part of extra cabin crews in the objective function (Eq. (3-6)), $\sum_{r\in R}\sum_{j_r^e\in J_r^e}(c_{j_r^e}+M)x_{j_r^e}$, although the insertion of M eliminates the impact of $c_{j_r^e}$, it is necessary to keep $c_{j_r^e}$ so that the TAFB information of extra cabin crew individual pairings could be recorded for the purpose of analysis.

cabin crew from the required class to each flight. The left-hand side of each row in Eqs. (3-8) is actually the total number of Class r cabin crews assigned to the flight (i.e., q_i^r). Secondly, Eqs. (3-9) play a pivotal role in avoiding unnecessary substitutions. In particular, each row of Eqs. (3-9) records the number of times of Class r being substituted by other classes on Flight i. Each substitution is coupled with a substitution penalty cost μ in the objective function. The relationship between c_{j_r} and μ ($c_{j_r} \ll \mu$) ensures that the model will (i) find the cost-least set of individual pairings for available cabin crews within each class to cover all flights in priority, and (ii) guarantee that no unnecessary substitutions will happen when there is enough manpower available. Once there is a shortage existing in a certain class on a flight when the manpower requirement increases along with flight fluctuation, CCS will function to support flight operations with a penalty μ. In light of this, the substitution penalty cost μ is also called the *flight fluctuation coefficient* because it helps hedge against the cabin crew requirement variation and manpower shortage arising during flight fluctuation. On the other hand, the relationship between μ and M ($\mu \ll M$) ensures that only when CCS fails to help complete all the duties, will the model turn to extra cabin crews to find feasible solutions. Regarding the value of μ and M, as the maximum TAFB pairing cost ($c_{j_r}, c_{j_r^e}$) is 7200 (recall that maximum 7200 minutes of TAFB are allowed for a pairing), this study sets μ as 500000 to ensure $c_{j_r} \ll \mu$, and M as 50000000 to ensure $\mu \ll M$.

The third group (Eqs. (3-10)) relates to the restriction of manpower availability, which ensures that the number of individual pairings generated for each class of available cabin crew will not exceed an upper limit. Actually, each individual pairing generated requires a cabin crew to operate. Therefore, the number of individual pairings used is applied to approximate the number of cabin crews required in the stage of pairing process. Moreover, this pre-set number constraint for each class of cabin crew could also be regarded as a belief that airlines expect at most how many pairings could be operated for one week based on their cabin crew manpower pool. Actually, these availability constraints are not hard constraints, as extra manpower is allowed with a penalty.

The last group (Eqs. (3-11) to (3-13)) guarantees that all variables are non-negative integers.

Besides, the proposed MICCPP-ACCS is utilized to calculate an important flight schedule manpower requirement benchmark for the managerial analyses presented in Section 3.3. Specifically, the minimum number of cabin crews of all classes required to completely cover a flight schedule with CCS (named as the *minimum total manpower demand with CCS*, denoted as MS) could be obtained. The calculation procedure is described as follows. First, the availability of available cabin crew for each class is set as zero (that is, each d_r is set as zero) for the proposed MICCPP-ACCS. Therefore, only $x_{j_r^e}$ exists in this d_r-Zero-MICCPP-ACCS model. As the generation of an extra cabin crew individual pairing ($x_{j_r^e}$) leads to a big penalty cost M, the number of total extra cabin crews required in the solution obtained from this d_r-Zero-MICCPP-ACCS (i.e., $\sum_{r\in R}\sum_{j_r^e\in J_r^e} x_{j_r^e}$) then stands for the MS for the flight schedule.

3.2.3. The Simplified MICCPP-A

The relationship between μ and M actually puts different emphasis on the application of CCS and extra cabin crews. In the proposed MICCPP-ACCS, CCS is always the primary strategy to tackle the problem of manpower shortage, while extra cabin crews are utilized to obtain feasible solutions only when CCS does not work. On the other hand, if the substitution penalty cost μ is far larger than the extra manpower penalty cost M (that is, $c_{j_r}, c_{j_r^e} \ll M \ll \mu$), the extra manpower employment is then always chosen by the model to overcome the dilemma of cabin crew insufficiency, while CCS is not allowed in this case (s_i^r is always equal to zero). In this regard, different classes of cabin crews will not substitute each other. Accordingly, the CCS-related constraints, the total satisfaction constraint (Eqs. (3-7)) and the minimum satisfaction constraint (Eqs. (3-8)), are no longer useful. Besides, as each class of cabin crews are scheduled independently in this case, the proposed MICCPP-ACCS is hence simplified and decomposed by cabin crew classes (r), which is denoted as MICCPP-A (see Eq. (3-14) to Eqs. (3-18)). In other words, MICCPP-A can be regarded as a simplified version of MICCPP-ACCS where the strategy of CCS is forbidden. Although MICCPP-ACCS is the primary model constructed in this work, the author would like to show that the individual cabin crew pairing model is in the format of MICCPP-A when the various cabin crew classes are scheduled independently (i.e., without the application of the CCS strategy).

(MICCPP-A) Min $\sum_{j_r \in J_r} c_{j_r} x_{j_r} + \sum_{j_r^e \in J_r^e} (c_{j_r^e} + M) x_{j_r^e}$ Eq. (3-14)

For each $r \in R$: s.t. $\sum_{j_r \in J_r} a_{ij_r} x_{j_r} + \sum_{j_r^e \in J_r^e} a_{ij_r^e} x_{j_r^e} \geq b_i^r, \quad \forall i \in F,$ Eqs. (3-15)

$\sum_{j_r \in J_r} x_{j_r} \leq d_r,$ Eqs. (3-16)

$x_{j_r} =$ non-negative integer, $\forall j_r \in J_r,$ Eqs. (3-17)

$x_{j_r^e} =$ non-negative integer, $\forall j_r^e \in J_r^e.$ Eqs. (3-18)

Table 3-2. The comparisons among TCCPP, MICCPP-ACCS and MICCPP-A.

Model	Flight requirements		Pairing type		Model features			
	Heterogeneous	Homogeneous	Team	Individual	Crew availability	CCS	No. of constraints	No. of networks
TCCPP		√	√				$\lvert F\rvert$	1
MICCPP-ACCS	√			√	√	√	$(2\lvert R\rvert + 1) \times \lvert F\rvert + \lvert R\rvert$	$\lvert R\rvert$
MICCPP-A	√			√	√		$\lvert F\rvert + 1$	1

In MICCPP-A, each class of cabin crews is planned independently because they are not permitted to substitute colleagues of other classes. For each class, the purpose of MICCPP-A is to identify a minimum-(pairing) cost set of individual pairings to satisfy all flight requirements of this class, under a certain level of availability. Besides, extra manpower variables ($x_{j_r^e}$) are introduced to ensure solution feasibility when the available cabin crews are insufficient. As The Airways prefers hiring the minimum extra cabin crews, a big M is imposed with the application of extra manpower ($x_{j_r^e}$), which is similar to MICCPP-ACCS. When the big M becomes smaller, it implies that the application of extra cabin crews is increasingly welcomed by the airline. When M =0, the airline shows no preferences between extra cabin crews and available cabin crews.

In short, MICCPP-A is a simplified version of MICCPP-ACCS without CCS. The outputs of these two models could be compared to demonstrate the advantages of the CCS strategy for airline operations. **Table 3-2** summarizes the comparisons among TCCPP, MICCPP-ACCS, and MICCPP-A. From **Table 3-2**, it is seen that the complexity of MICCPP-ACCS is much larger than MICCPP-A and TCCPP.

Table 3-3. The three flight requirement benchmarks for a flight schedule.

Benchmarks	Dimension	Obtained from		Parameter setting	
		MICCPP-ACCS	MICCPP-A	d_r	b_i^r
$MS = \sum_{r\in R}\sum_{j_r^e\in J_r^e} x_{j_r^e}$	For all classes	√		0	b_i^r
$MC_r = \sum_{j_r^e\in J_r^e} x_{j_r^e}$	For Class r		√	0	b_i^r
$MM_r = \sum_{j_r^e\in J_r^e} x_{j_r^e}$	For Class r		√	0	1

Furthermore, two insightful flight schedule manpower requirement benchmarks could be obtained from MICCPP-A. Note that although they can also be obtained from MICCPP-ACCS, MICCPP-A is utilized to demonstrate them in a clearer way because these two benchmarks both relate to a specific Class r, rather than the whole of all classes. They are i) the minimum number of Class r cabin crews required for a flight schedule without CCS (named as the *minimum manpower demand for Class r without CCS*, denoted as MC_r), and ii) the minimum number of class r cabin crews required to cover each flight at least by one crew member for a flight schedule without substitution (named as the *minimum satisfaction constraint manpower demand for Class r*, denoted as MM_r). The approaches to obtain the two benchmarks are described as follows. For MC_r, the number of extra cabin crews needed in the solution obtained from MICCPP-A where no available manpower is used (setting d_r as 0) represents MC_r. For MM_r, all flight manpower requirements are arbitrarily set as one (setting b_i^r $(\forall i \in F)$ as 1), to simulate the minimum satisfaction situation. Similarly, there is no available cabin crew applied (setting d_r as 0). After solving the MICCPP-A model, the population of extra cabin crews required in the solution is hence MM_r. Generally, MM_r is smaller than MC_r. Only when all flights require just one Class r cabin crew, will MM_r equal MC_r. Besides, it is noted that the MM_r values for all classes are the same regarding a flight schedule. **Table 3-3** concludes the model used and parameter setting to obtain the three benchmarks. By comparing the airline manpower availability levels with the three generated benchmarks, some insightful managerial implications could be derived, as will be explained in Section 3.3.

3.3. Manpower Availability-Requirement Analysis

Applying the proposed MICCPP-ACCS, this sub-chapter presents analyses about the relationship between cabin crew availability levels (that is, the maximum number of pairings allowed for a week) and the obtained flight schedule manpower requirement benchmarks, in order to derive some managerial insights for airline cabin crew management. First of all, recall the three manpower requirement benchmarks built for a flight schedule in Section 3.2: The minimum total manpower demand with CCS (MS), the minimum manpower demand for Class r without CCS (MC_r), and the minimum satisfaction constraint manpower demand for Class *r* (MM_r). Besides, TA is used to represent the summation of current available cabin crews of all classes ($TA = \sum_{r \in R} d_r$). Obviously, Class *r* becomes insufficient when the quantity of available Class *r* cabin crews is less than MC_r (i.e., $d_r < MC_r$), which implies that the tactics of CCS or hiring extra cabin crews should be taken to sustain the normal operations of the flight schedule. In reality, the specific managerial strategies (such as the application of CCS, the employment of extra manpower, or both) to be adopted depend on the particular relationships between the manpower availability levels (i.e., TA, d_r) with the benchmarks (i.e., MS, MC_r, MM_r) (e.g., smaller, equal, or larger). For instance, the employment of Class *r* extra manpower is inevitable once d_r is smaller than MM_r, which means that the current Class *r* available cabin crews fail to respect the minimum satisfaction constraint regulated by the CCS mechanism. During flight fluctuation, the manpower requirement benchmarks vary along time, leading to different availability-requirement relationships. Consequently, it is crucial to excavate the characteristics of various scenarios under the diverse availability-requirement relationships, which is summarized in **Table 3-4**. Detailed explanations for each scenario are illustrated as follows. In the following discussions, R^* is used to represent the set of classes where $d_r < MM_r$. Besides, subsets R^1, R^2, R^3, R^4 and R^5 that are used for analysis are defined in **Table 3-4**.

Table 3-4. The impact of availability-requirement relationship on cabin crew management.

<table>
<tr><th colspan="4">Availability-requirement relationship</th><th rowspan="2">Scenario</th><th colspan="3">Implications on manpower management</th></tr>
<tr><th>First-layer (A)</th><th>Second-layer (B)</th><th colspan="2">Third-layer (C)</th><th>Manpower shortage</th><th>CCS</th><th>Extra manpower</th></tr>
<tr><td rowspan="4">(A1) If $TA < MS$</td><td rowspan="2">(B1) If for some $r \in R,\ d_r > MC_r$ (this subset is denoted as R^1)</td><td colspan="2">(C1) Denote the subset of classes where $d_r < MC_r$ as $R^2 (R^2 \subseteq (R - R^1))$. If for all $r \in R^2$, $MM_r = MC_r$</td><td>1</td><td>√</td><td></td><td>√</td></tr>
<tr><td colspan="2">(C2) If for some $r \in R^2$, $MM_r < MC_r$ (this subset is denoted as $R^3 (R^3 \subseteq R^2)$)</td><td>2</td><td>√</td><td>√</td><td>√</td></tr>
<tr><td rowspan="2">(B2) If for all $r \in R, d_r \leq MC_r$</td><td colspan="2">(C3) If $MS = \sum_{r \in R} MC_r$</td><td>3</td><td>√</td><td></td><td>√</td></tr>
<tr><td colspan="2">(C4) If $MS < \sum_{r \in R} MC_r$</td><td>4</td><td>√</td><td>√</td><td>√</td></tr>
<tr><td rowspan="4">(A2) If $TA \geq MS$</td><td rowspan="3">(B3) If for some $r \in R,\ d_r < MC_r$ (this subset is denoted as R^4)</td><td colspan="2">(C5) If for all $r \in R^4, d_r \geq MM_r$</td><td>5</td><td>√</td><td>√</td><td></td></tr>
<tr><td rowspan="2">If for some $r \in R^4, d_r < MM_r$</td><td>(C6) If for all $r \in R^4$, $MM_r = MC_r$</td><td>6</td><td>√</td><td></td><td>√</td></tr>
<tr><td>(C7) If for some $r \in R^4$, $MM_r < MC_r$ (this subset is denoted as $R^5 (R^5 \subseteq R^4)$)</td><td>7</td><td>√</td><td>√</td><td>√</td></tr>
<tr><td colspan="3">(B4) If for all $r \in R, d_r \geq MC_r$</td><td>8</td><td colspan="3">No manpower shortage</td></tr>
</table>

A1. $[TA < MS]$. In this case, the total available manpower is insufficient, failing to complete the flight schedule even applying CCS. Herein, extra cabin crews are inevitable to find feasible solutions, while CCS is possibly needed as discussed in the following (Scenarios 1 to 4).

B1. [For some $r \in R$, $d_r > MC_r$ $(r \in R^1)$]. In this situation, the number of available cabin crews for class $r \in R^1$ is larger than the minimum requirement MC_r. Therefore, the class $r \in R^1$ has exceeding available staff (the exceeding number is $d_r - MC_r$). However, whether CCS could be utilized to solve the manpower shortage problem depends on the characteristics of the classes that are in a shortage, as Scenario 1 and Scenario 2.

C1. **<u>Scenario 1</u>** [For all r where $d_r < MC_r$ $(r \in R^2(R^2 \subseteq (R - R^1)))$, $MM_r = MC_r$]. In this scenario, for the classes $r \in R^2$ which are insufficient, the minimum manpower requirement MC_r is equal to the minimum satisfaction constraint manpower demand MM_r. Therefore, $R^2 = R^*$. As a result, for each class $r \in R^2(R^*)$, it is enough to employ the number of $(MM_r - d_r)$ extra staff to satisfy the minimum satisfaction constraint, while CCS would not function.

C2. **<u>Scenario 2</u>** [For some $r \in R^2, MM_r < MC_r$ $(r \in R^3(R^3 \subseteq R^2))$]. In this scenario, because the minimum manpower requirement for class $r \in R^3$ is higher than the minimum satisfaction constraint manpower demand (i.e., $MC_r > MM_r$), the manpower from other classes could be utilized as a "substituter" to fulfil some jobs for those from class $r \in R^3$. Besides, extra manpower is necessary to build feasible solution. The total number of extra cabin crews needed is $\text{Max}\{\sum_{r \in R^*}(MM_r - d_r), (MS - TA)\}$.

B2. [For all $r \in R, d_r \leq MC_r$]. In this situation, the number of available cabin crews for each class is smaller than or equal to the minimum requirement MC_r. Whether CCS could play an effective role in hedging against manpower shortage depends on the relationship between MS and $\sum_{r \in R} MC_r$, as discussed in Scenario 3 and Scenario 4.

C3. **<u>Scenario 3</u>** [$MS = \sum_{r \in R} MC_r$]. $MS = \sum_{r \in R} MC_r$ means that the minimum total manpower demand with the application of CCS is the same as the case where CCS is not employed. That is, the minimum overall manpower requirement for the flight schedule involves no CCS. In this scenario, the number $(MC_r - d_r)$ of extra cabin crews for each class $r \in R$ will be employed to facilitate the flight operations. No CCS is needed.

C4. **<u>Scenario 4</u>** [$MS < \sum_{r \in R} MC_r$]. $MS < \sum_{r \in R} MC_r$ implies that the minimum total manpower demand with the application of CCS is lower than the case where CCS is not employed. In other words, CCS succeeds in reducing the minimum total manpower demand. Therefore, the total

Max$\{\sum_{r \in R^*}(MM_r - d_r), (MS - TA)\}$ extra cabin crews are demanded to help fulfill all the duties with crew substitutions.

A2. $[TA \geq MS]$. In this case, the total available manpower has the potential to cover all flight requirements. However, whether the available manpower is in a shortage, and whether CCS or extra manpower is needed should be further examined (Scenarios 5 to 8).

B3. [For some $r \in R, d_r < MC_r$ $(r \in R^4)$]. In this situation, the number of available cabin crews for class $r \in R^4$ is smaller than the minimum requirement MC_r, which means that this class is insufficient to cover all flight requirements on its own. Therefore, manpower shortage exists in this situation. Whether CCS or extra manpower is needed is further divided into three scenarios (5, 6, and 7) as follows.

C5. **Scenario 5** [For all $r \in R^4, d_r \geq MM_r$]. In this scenario, as $TA \geq MS$ and the available manpower of each class is sufficient to cover the minimum satisfaction constraints (i.e., $d_r \geq MM_r$), although certain classes are in a shortage, the application of CCS will assist in completing the whole flight operations without the employment of extra cabin crews.

C6. **Scenario 6** [For some $r \in R^4, d_r < MM_r$; and for all $r \in R^4$, $MM_r = MC_r$]. In this scenario, for the classes which are insufficient, the minimum manpower requirement MC_r is equal to the minimum satisfaction constraint manpower demand MM_r. Therefore, $R^4 = R^*$. As a result, it is sufficient to employ class $r \in R^*$ (R^4) extra staff to satisfy the minimum satisfaction constraints. The number of extra staffs needed for class $r \in R^*(R^4)$ is equal to $(MM_r - d_r)$. No CCS is needed.

C7. **Scenario 7** [For some $r \in R^4, d_r < MM_r$; and for some $r \in R^4$, $MM_r < MC_r$ $(r \in R^5(R^5 \subseteq R^4))$]. Extra manpower is necessary for class $r \in R^*$ with the number of $(MM_r - d_r)$. At the same time, some duties of class $r \in R^5$ could be operated by the manpower of other class with the strategy of CCS due to the fact that $MM_r < MC_r$ (for $r \in R^5$).

B4. **Scenario 8** [For all $r \in R, d_r \geq MC_r$]. In this situation, the number of available cabin crews for all classes $r \in R$ are larger than the minimum requirement MC_r, which means that no manpower shortage exists. Accordingly, no CCS or extra manpower is required.

In conclusion, the analysis in this sub-chapter demonstrates that the relationship between cabin crew availability levels (that is, the maximum number of pairings allowed for a week) and flight schedule manpower requirement benchmarks is critical to determine which cabin crew management strategies should be adopted (for example, whether CCS or extra cabin crews are required). Although the focus of this research is not on the daily manpower availability at this stage, it is important to demonstrate that the manpower availability level is indeed a crucial determinant in cabin crew management, which is believed to provide some useful insights for airlines. Through comprehensive and careful analysis, eight scenarios are identified. Specifically, the strategy of CCS is especially valuable in Scenarios 2, 4, 5, and 7 in dealing with the dilemma of cabin crew shortage, and alleviating the dependence on extra manpower during the manpower demand variation caused by flight fluctuation. The summary of extra manpower demand of MICCPP-ACCS in each scenario is summarized in the second column of **Table 3-5**, together with the comparisons between that of MICCPP-A without the function of CCS. The last column specifies whether CCS helps in reducing the demand for extra manpower compared with the situation where CCS is not formulated. Specifically, the extra manpower requirement declines when CCS succeeds to function (Scenarios 2, 4, 5, and 7). In Scenario 5, the extra manpower demand is even eliminated. Therefore, it is shown that CCS plays a pivotal role in dealing with the disruption brought by flight fluctuation through manpower utilization improvement.

Finally, it should be noted that flights generally require more than one cabin crews of each class. Hence, the value of MC_r is usually larger than MM_r. Therefore, Scenarios 1 and 6 are special cases where all flights on the schedule need only one cabin crew of the considered classes (that is, for the considered class r and all flights $i \in F$, b_i^r=1; then, $MM_r = MC_r$).

Table 3-5. Summary of extra manpower demand in each scenario of MICCPP-ACCS and MICCPP-A.

Scenario	Total extra manpower demand obtained from the model			CCS reduce extra manpower demand
	MICCPP-ACCS	MICCPP-A	Identical	
1	$\sum_{r\in R^*}(MM_r - d_r)$[#]	$\sum_{r\in R^2}(MC_r - d_r)$	√	
2	Max{$\sum_{r\in R^*}(MM_r - d_r)$, $(MS - TA)$}	$\sum_{r\in R^2}(MC_r - d_r)$		√
3	$\sum_{r\in R}(MC_r - d_r)$	$\sum_{r\in R}(MC_r - d_r)$	√	
4	Max{$\sum_{r\in R^*}(MM_r - d_r)$, $(MS - TA)$}	$\sum_{r\in R}(MC_r - d_r)$		√
5	0	$\sum_{r\in R^4}(MC_r - d_r)$		√
6	$\sum_{r\in R^*}(MM_r - d_r)$[##]	$\sum_{r\in R^4}(MC_r - d_r)$	√	
7	$\sum_{r\in R^*}(MM_r - d_r)$	$\sum_{r\in R^4}(MC_r - d_r)$		√
8	0	0	√	

[#]In Scenario 1, $R^2 = R^*$ and $MM_r = MC_r$.
[##] In Scenario 6, $R^4 = R^*$ and $MM_r = MC_r$.

3.4. Solution Approach

In the literature, the continuous relaxation of the CPP is generally solved by column generation (e.g., Lavoie et al., 1988, Saddoune et al., 2013), a popular continuous optimization technique that can solve large-scale linear programming problems without the difficulty of explicitly considering all the columns (Barnhart et al., 1998; Liang et al., 2018). The problem is divided into a restricted master problem (RMP) and a pricing problem (PP). The RMP is initiated by an initial feasible solution with a restricted number of columns, while the PP generates better columns to iteratively update the RMP column pool. The whole iterative process terminates when no better columns could be found. The current optimal RMP solution is also optimal for the whole problem. The proposed model MICCPP-ACCS has exponentially many variables (columns). Therefore, a customized branch-and-price process is built to identify the optimal solutions for MICCPP-ACCS[13], which is illustrated in this sub-chapter. Besides,

[13] Column generation is also applied to solve TCCPP and the simplified MICCPP-A in a similar but much simpler manner. For brevity, details are not shown in the thesis.

it is noted that as the main focus of this work is to propose a new cabin crew pairing generation model, rather than proposing solution methodological advancements, the standard solution approach is thus applied.

3.4.1. Restricted Master Problem

The RMP is the linear relaxed version of MICCPP-ACCS by releasing the integrality constraints Eqs. (3-11) to (3-13) into non-negative restrictions. The column in the model associated with each decision variable (x_{j_r} and $x_{j_r^e}$) is denoted as $\boldsymbol{\xi_x}$, a $((2|R|+1) \times |F| + |R|) \times 1$ vector with elements of 0 or 1. Different from TCCPP where each column simply represents a team pairing j_t, the columns in MICCPP-ACCS are more complicated. For the $\xi_{x_{j_r}}$ of x_{j_r}, the elements in Eqs. (3-7), in the *rth* set of Eqs. (3-8), and in the *rth* set of Eqs. (3-9) represent the corresponding individual pairing j_r, while the element in the *rth* row of Eqs. (3-10) equals one. All the remaining elements in $\xi_{x_{j_r}}$ are zero. For $x_{j_r^e}$, $\xi_{x_{j_r^e}}$ is similar to $\xi_{x_{j_r}}$, except that the element in the *rth* row of Eqs. (3-10) equals zero.

Due to the limitation of available cabin crews (that is, Eqs. (3-10)), it is difficult to identify an initial feasible solution using the available manpower, especially when some classes are insufficient. Herein, an efficient tailored initiation methodology called the *dynamic programming based initialization algorithm* (DPIA) is proposed, to quickly initiate the RMP using the unlimited extra cabin crews. In DPIA, a set of legal individual pairings (Q) that covers each flight at least once is identified based on the constructed duty-based networks. Note that the networks for extra cabin crews are identical as those for available cabin crews. **Table 3-6** shows the pseudo-code of DPIA, where U is the set of unprocessed partial paths and O is the set of covered flights. In particular, U is initialized by adding the trivial partial path only containing the source node *s*.

As there is no upper limit on extra manpower, the individual pairings generated in

Q could be applied to each class of extra cabin crews to cover all flight requirements, satisfying all the constraints in Eqs. (3-7)- Eqs. (3-13). Therefore, the RMP is initiated by inserting the variables $x_{j_r^e}$ ($j_r^e \in Q$) and corresponding columns $\xi_{x_{j_r^e}}$ into the pool, which is solved by the Simplex method. The dual prices associated with each constraint obtained are then passed to the PP.

Table 3-6. Dynamic programming based initialization algorithm (DPIA).

Begin
    U ={(*s*)}, $O = \emptyset$, $Q = \emptyset$;
    While the size of $O \neq$ the number of flights to be scheduled, **do**
    Begin
        Select the last element $L \in U$, and delete it from U;
        Extend L to all possible directions if no resource ($\tau \in \Theta$) is violated;
        For each newly generated (partial) path H, **do**
        Begin
            If H ends at the sink node *m*, **then**
                If any flight z in H is not contained in O, **then**
                    add z in O, and add H in Q;
            Else
                Add H to U;
        End
    End
End

3.4.2. Pricing Problem

In each iteration, the aim of PP is to find promising columns with negative reduced costs to update the RMP column pool. The reduced costs (RC_x) of decision variables x_{j_r} and $x_{j_r^e}$ are formulated as Eq. (3-19) and Eq. (3-20). Specifically, π_i is the dual price for the i_{th} row (flight i) of Eqs. (3-7), λ_i^r is the dual price for the i_{th} row of the r_{th} set (flight i, Class r) of Eqs. (3-8), θ_i^r is the dual price for the i_{th} row of the r_{th} set (flight i, Class r) of Eqs. (3-9), and φ_r is the dual price for the r_{th} row (Class r) of Eqs. (3-10).

For x_{j_r} $\quad RC_{x_{j_r}} = c_{j_r} + \sum_{i \in F}(-\pi_i - \lambda_i^r - \theta_i^r)a_{ij_r} - \varphi_r.$ $\quad$ Eq. (3-19)

For $x_{j_r^e}$ $\quad RC_{x_{j_r^e}} = c_{j_r^e} + \sum_{i \in F}(-\pi_i - \lambda_i^r - \theta_i^r)a_{ij_r^e} + M.$ $\quad$ Eq. (3-20)

For $RC_{x_{j_r}}$, the first part (c_{j_r}) is the TAFB cost of j_r. The second part

$(\sum_{i \in F}(-\pi_i - \lambda_i^r - \theta_i^r)a_{ij_r})$ is the sum of negative dual prices of each flight covered in j_r, where $(-\pi_i - \lambda_i^r - \theta_i^r)$ is called the *flight negative dual price cost* (FNDPC) for flight *i*. The third part (φ_r) is the negative dual price for the corresponding Class *r*, which is unrelated with j_r. For $x_{j_r^e}$, $RC_{x_{j_r^e}}$ is similar to $RC_{x_{j_r}}$, except that the third part (M) is the big penalty cost induced by the generation of an extra cabin crew, which is also irrelevant with the feature of j_r^e. In addition, the number of substitution recording variable s_i^r is a constant as $(|F| \times |R|)$, and the reduced cost for s_i^r is $(\mu - \theta_i^r)$.

Now, for each class of available cabin crews, it is assumed that in the duty-based network, the arc cost $ac_{arc_{(n_r,n_r')}}$ is equal to the time duration of the arc (as in Eq. (3-21) to Eq. (3-23)), while the duty node cost $nc_{d_k^r}$ equals the aggregated FNDPC of the flights contained in d_k^r (see Eq. (3-24)). Besides, there is no cost for the source/sink node (Eq. (3-25)). Therefore, the total arc cost for a resource-feasible *s*-*m* path (tac_{j_r}) is the TAFB of j_r (as in Eq. (3-26)). Besides, the total node cost tnc_{j_r} for path j_r is the sum of FNDPC of all the flights contained in j_r (Eq. (3-27)). Furthermore, the total cost for path j_r (tc_{j_r}) is formulated as Eq. (3-28), as the summation of total arc cost, total node cost, together with $-\varphi_r$, which is exactly the reduced cost $RC_{x_{j_r}}$ in Eq. (3-19). Accordingly, the PP is transformed to solve a resource constrained shortest path problem (RCSPP) in each class of duty-based network, to identify new paths with negative tc_{j_r} $(RC_{x_{j_r}})$. The label correcting algorithm is applied to solve the RCSPP problem, which is widely used in the pricing problem of column generation, like Irnich and Desaulniers (2005). With the labels recording costs and resource consumptions, the state of each path in the network could be analyzed to dominate the "worse" paths and the most cost-efficient legal path can be selected. The negative-cost solution obtained from RCSPP corresponds to a potential individual pairing to improve the RMP. The next iteration is triggered by adding the identified new variable into the RMP pool, until no better paths could be found. The PP mechanism for $x_{j_r^e}$ is similar to that for x_{j_r}, except that the total path cost consists of total arc cost, total node cost, together with M, rather than $-\varphi_r$. Finally, the column generation process is embedded into a branch-and-bound scheme to obtain integer solutions.

Cost of a rest arc	$ac_{arc_{(d^r_{k_1}, d^r_{k_2})}} =$ duration from the end of $d^r_{k_1}$ to the end of $d^r_{k_2}$.	Eq. (3-21)
Cost of a starting arc	$ac_{arc_{(s, d^r_k)}} =$ the duration of d^r_k.	Eq. (3-22)
Cost of an ending arc	$ac_{arc_{(d^r_k, t)}} = 0$.	Eq. (3-23)
Cost of a duty node	$nc_{d^r_k} = \sum_{i \in F_{d^r_k}} (-\pi_i - \lambda^r_i - \theta^r_i)$.	Eq. (3-24)
Cost of source/sink node	$nc_s, nc_m = 0$.	Eq. (3-25)
Total arc cost of path j_r	$tac_{j_r} = \sum_{(n_r, n'_r) \in j_r} ac_{(n_r, n'_r)} =$ TAFB of path (pairing) $j_r = c_{j_r}$.	Eq. (3-26)
Total node cost of path j_r	$tnc_{j_r} = \sum_{d^r_k \in j_r} nc_{d^r_k} = \sum_{d^r_k \in j_r} \sum_{i \in F_{d^r_k}} (-\pi_i - \lambda^r_i - \theta^r_i)$.	Eq. (3-27)
Total cost of path j_r	$tc_{j_r} = tac_{j_r} + tnc_{j_r} - \varphi_r = RC_{x_{j_r}}$.	Eq. (3-28)

3.5. Computational Experiments

This sub-chapter presents analyses that demonstrate the superior performance of the proposed MICCPP-ACCS model through computational experiments based on real-world collected flight schedules. Experiments were conducted on a PC with Windows 7 operation system and Intel (R) Core (TM) i7-4790 @ 3.60 GHz (32 GB RAM). The implementations are coded in Java programming language. The RMP is solved using CPLEX Concert Technology in IBM ILOG CPLEX Optimization Studio (Version 12.6.3). Firstly, the real flight schedules selected in the study are described in Section 3.5.1. Then, the initial flight schedules are preprocessed for experiments and the characteristics of the derived instances are introduced in Section 3.5.2. Thirdly, the manpower requirement benchmarks for the derived instances are obtained, based on which the tested cabin crew availability levels are generated in Section 3.5.3. With the derived manpower availability levels, Section 3.5.4 demonstrates the applicability and high efficiency of the novel MICCPP-ACCS over TCCPP, especially in terms of cabin crew utilization and associated costs. Besides, Section 3.5.5 compares the performance of MICCPP-ACCS with the simplified version of MICCPP-A to illustrate the effect of CCS. Lastly, the special availability-requirement Scenarios 1 and 6 are tested in Section 3.5.6.

3.5.1. Selected Flight Schedules

The main focus is to show the merits of the proposed individual pairing approach (i.e., MICCPP-ACCS) in terms of manpower utilization improvement and cost reduction. Therefore, considering the large scale and complexity of MICCPP-ACCS, the proposed model is tested using a relatively small-scale set of instances based on The Airways. The Airways' flight network mainly has a hub-and-spoke structure. There are more than twelve thousand four-class ($|R| = 4$) cabin crews working for The Airways, which makes cabin crew management significantly challenging.

The tested instances are derived from an eight-week flight schedule of a route between the home base Hong Kong (HKG) and Singapore (SIN). Each week of schedule is an independent instance. Therefore, the proposed models are run for each instance to obtain solutions for comparison. Note that instead of solving a dated monthly pairing problem, this study aims to show the performances of the proposed pairing generation approach using these eight independent week-instances. The flight data, for example, flight number, departure time, arrival time, and aircraft type used, are collected from the website of The Airways, spanning from 19, Nov 2017 to 13, Jan 2018. The considered HKG-SIN route averagely takes 235.7 minutes, involving five aircraft types of Airbus Industrie A330-300, Airbus Industrie A350-900, Boeing 777-200/200ER, Boeing 777-300, and Boeing 777-300ER, denoted as Type 1, Type 2, Type 3, Type 4, and Type 5 respectively. Particularly, Type 1 has three different cabin layouts, denoted as Type 1-1, Type 1-2, and Type 1-3, while Type 5 has two, denoted as Type 5-1 and Type 5-2. The details of cabin layouts, seat capacities, and cabin crew requirements are illustrated in **Table B-1** and **Table B-2** (see Appendix B). Considering that the flight schedules collected from The Airways website only give the aircraft type used without the specific layouts, the experiments randomly select layouts for Type 1 flights and Type 5 flights. Besides, according to the average salary statistics in the service industry in Hong Kong[14], the weekly fixed payment for an available cabin crew and extra cabin crew are approximated as 3,000 and 6,000 Hong Kong dollars, respectively ($c_{fa} = 3{,}000$ and $c_{fe} = 6{,}000$).

Table 3-7. Number of flights and aircraft types contained in the selected flight schedules.

Week	No. of flights	No. of aircraft of each type contained									
		Type 1	%	Type 2	%	Type 3	%	Type 4	%	Type 5	%
Week 1	105	13	12.4%	29	27.6%	3	2.9%	24	22.9%	36	34.3%
Week 2	106	11	10.4%	32	30.2%	5	4.7%	26	24.5%	32	30.2%
Week 3	100	7	7.0%	34	34.0%	7	7.0%	30	30.0%	22	22.0%
Week 4	103	22	21.4%	28	27.2%	3	2.9%	32	31.1%	18	17.5%
Week 5	104	13	12.5%	38	36.5%	8	7.7%	28	26.9%	17	16.4%
Week 6	100	20	20.0%	39	39.0%	5	5.0%	16	16.0%	20	20.0%
Week 7	109	30	27.5%	39	35.8%	7	6.4%	7	6.4%	26	23.9%
Week 8	110	28	25.5%	41	37.3%	5	4.6%	19	17.3%	17	15.5%

Table 3-7 summarizes the number of flights and the number of each type of aircraft contained in the selected weekly schedules. Obviously, there are mixed types of aircraft in a flight schedule, which requires the individual modelling approach for cabin crews. Besides, it could be seen that the flight frequency and aircraft types involved typically fluctuate over time. One typical flight (Flight 636) is used to demonstrate the flight fluctuation in **Figure 3-4**, with the horizontal axis representing the day of time and the vertical axis standing for the aircraft type used. In specific, the vertical axis value of zero implies that there is no flight on that day, while an integer positive value means that Flight 636 is operated on that day with the corresponding type of aircraft. As can be seen, during the considered period, Flight 636 is not operated on three days (19 Nov, 26 Nov, and 03 Dec). Besides, five types of aircraft are used to conduct Flight 636. For example, a Type 5 aircraft (Boeing 777-300ER) is assigned on 28 Dec, while a Type 2 aircraft (Airbus Industrie A350-900) is appointed on 29 Dec.

[14] https://www.censtatd.gov.hk/hkstat/sub/sp210.jsp?tableID=028&ID=0&productType=8 (Retrieved in December, 2017).

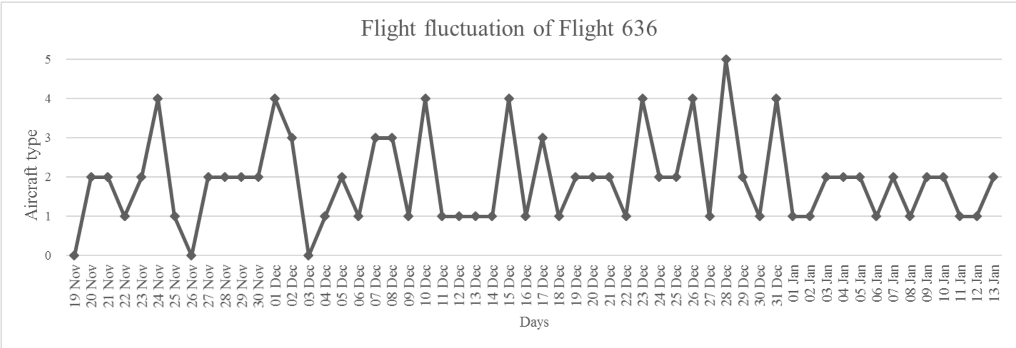

Figure 3-4. An example of flight fluctuation.

3.5.2. Preprocessing and Instance Characteristics

As the objective is to compare the performance of the proposed MICCPP-ACCS with TCCPP, it is necessary to pre-process the raw flight schedules to ensure feasible solutions for TCCPP. As mentioned, TCCPP is solved within each separate aircraft type; therefore, each original weekly flight schedule in **Table 3-7** is decomposed by aircraft types into five sub-schedules for each type of TCCPP. For example, Week 1 schedule (105 flights) is decomposed into a Type 1 sub-schedule (13 flights) for Type 1 TCCPP, a Type 2 sub-schedule (29 flights) for Type 2 TCCPP, a Type 3 sub-schedule (3 flights) for Type 3 TCCPP, a Type 4 sub-schedule (24 flights) for Type 4 TCCPP, and a Type 5 sub-schedule (36 flights) for Type 5 TCCPP. Then, within each separate sub-schedule, those flights that cannot be covered by any feasible pairing are examined and deleted. This is because a partial set of flights of The Airways is considered for computational experiments. Thus, some of the flights selected might not appear in any feasible path in the constructed duty-based network. Moreover, after the flight schedule is decomposed by aircraft types (as TCCPP is solved within each separate aircraft type), the flight un-coverage problem becomes severer. Therefore, to facilitate analyses and achieve the comparison between MICCPP-ACCS and TCCPP, the selected flight schedules are preprocessed to delete the uncovered flights. The processed instances are shown in **Table 3-8**, and the number of uncovered flights for each schedule is summarized in the fourth column of the table. In addition, as could be seen from **Table 3-7**, the number of flights using certain aircraft types is much lower than those using other types. For example, for each selected weekly schedule, more than twenty flights apply Type 2 aircraft, while only a few flights (less than ten) use Type 3 aircraft. Therefore, it is reasonable that the number of remained flights after preprocessing for Type 3 aircraft could be much smaller than that for Type 2 aircraft. From **Table 3-8**, it could be seen that for three instances (I1, I2, and I4), no flights using Type 3 aircraft are remained. Accordingly, the number of feasible paths in the corresponding networks could become very small (see **Table 3-9**). This could also show the shortcoming of solving the cabin crew pairing problem by decomposing the flight schedule according to aircraft types in the traditional cabin CPP practice. Therefore, regarding Week 1 schedule, 4, 27, 0, 21, and 32 flights remain for Types 1, 2, 3, 4, and 5 TCCPP, respectively. The whole set of these remaining flights (84 flights) forms the real test instance 1 (I1). For ease of expression, the instances are denoted as Ix-M when the proposed MICCPP-ACCS is tested (as in the second column of **Table 3-8**), while each aircraft type of instance for TCCPP is denoted as Ix-Ty (as in the 5th, 7th, 9th, 11th, and 13th columns of **Table 3-8**). For example, I1 for MICCPP-ACCS is I1-M, while Type 1 of I1 for TCCPP is I1-T1.

Table 3-9 compares the instance characteristics of the proposed MICCPP-ACCS with TCCPP in terms of the number of duties, arcs, and feasible paths (pairings). Obviously, the problem scale and complexity are much higher in the proposed MICCPP-ACCS. With fewer flights considered, the number of duties, arcs, and feasible paths in TCCPP are much less than those in the MICCPP-ACCS instances. On average, there are 114.63 duties in MICCPP-ACCS, while only 14 in type 1 TCCPP, 32.13 in type 2 TCCPP, 2.25 in type 3 TCCPP, 23.88 in type 4 TCCPP, and 23.63 in type 5 TCCPP. Besides, MICCPP-ACCS averagely has 247.02% more arcs than the sum of all five types of TCCPP. With a larger set of nodes and arcs, the number of candidate itineraries for MICCPP-ACCS is exponentially higher than that for the sum of all five types of TCCPP (67.04 times averagely). Consequently, larger computational efforts should be paid when solving the proposed MICCPP-ACCS. Note that the instances for the simplified MICCPP-A are identical with those for MICCPP-ACCS without decomposition by aircraft types, but MICCPP-A solves for each cabin class separately without the function of CCS. **Table C-1** (see Appendix C) summarizes the number of constraints and size of the initial pool for each model, which also shows the difficulty of MICCPP-ACCS.

Table 3-8. Number of flights contained in the processed instances.

Instance	MICCPP-ACCS	No. of flights	No. of uncovered flights	TCCPP									
				Type 1	No. of flights	Type 2	No. of flights	Type 3	No. of flights	Type 4	No. of flights	Type 5	No. of flights
I1	I1-M	84	21	I1-T1	4	I1-T2	27	I1-T3	0	I1-T4	21	I1-T5	32
I2	I2-M	85	21	I2-T1	5	I2-T2	29	I2-T3	0	I2-T4	23	I2-T5	28
I3	I3-M	77	23	I3-T1	0	I3-T2	29	I3-T3	2	I3-T4	26	I3-T5	20
I4	I4-M	85	18	I4-T1	18	I4-T2	25	I4-T3	0	I4-T4	28	I4-T5	14
I5	I5-M	81	23	I5-T1	7	I5-T2	33	I5-T3	6	I5-T4	24	I5-T5	11
I6	I6-M	77	23	I6-T1	14	I6-T2	33	I6-T3	2	I6-T4	14	I6-T5	14
I7	I7-M	92	17	I7-T1	27	I7-T2	34	I7-T3	5	I7-T4	2	I7-T5	24
I8	I8-M	83	27	I8-T1	21	I8-T2	37	I8-T3	2	I8-T4	10	I8-T5	13

Table 3-9. Instance characteristics of MICCPP-ACCS and TCCPP.

MICCPP-ACCS				TCCPP															
Instance	Duty	Arc	Feasible paths	Type 1 Instance	Duty	Arc	Feasible paths	Type 2 Instance	Duty	Arc	Feasible paths	Type 3 Instance	Duty	Arc	Feasible paths	Type 4 Instance	Duty	Arc	Feasible paths	Type 5 Instance	Duty	Arc	Feasible paths
I1-M	121	1104	50803	I1-T1	4	6	2	I1-T2	28	81	134	I1-T3	0	0	0	I1-T4	27	77	130	I1-T5	43	174	981
I2-M	120	1069	50150	I2-T1	5	8	3	I2-T2	31	99	184	I2-T3	0	0	0	I2-T4	30	94	198	I2-T5	36	118	380
I3-M	104	862	27215	I3-T1	0	0	0	I3-T2	30	92	186	I3-T3	2	3	1	I3-T4	33	119	316	I3-T5	23	60	86
I4-M	121	1158	59619	I4-T1	23	75	57	I4-T2	25	68	86	I4-T3	0	0	0	I4-T4	35	126	424	I4-T5	16	36	32
I5-M	109	882	32422	I5-T1	7	13	6	I5-T2	36	129	383	I5-T3	6	9	3	I5-T4	32	105	248	I5-T5	12	25	16
I6-M	103	787	21259	I6-T1	16	35	31	I6-T2	34	110	282	I6-T3	2	3	1	I6-T4	18	44	25	I6-T5	17	40	49
I7-M	128	1228	67625	I7-T1	33	105	227	I7-T2	35	113	262	I7-T3	6	9	3	I7-T4	3	4	1	I7-T5	27	86	190
I8-M	111	953	38330	I8-T1	24	60	60	I8-T2	38	133	377	I8-T3	2	3	1	I8-T4	13	24	11	I8-T5	15	31	24
Average	115	1005	43428		14	38	48		32	103	237		2	3	1		24	74	169		24	71	220

3.5.3. Benchmarks and Availability Levels

Based on the details described in **Table 3-3**, the manpower requirement benchmarks for each instance are obtained as illustrated in **Table 3-10**, which shows the variation in the (minimum) manpower demand during flight fluctuation. For the first instance with 84 flights, the minimum total manpower demand with CCS (MS) is 184, less than the summation of the minimum manpower demand without CCS of all classes (i.e., $\sum_{r\in R} MC_r$=189), which implies that the application of CCS succeeds in reducing the minimum total manpower demand by 5. However, in I3, $MS = \sum_{r\in R} MC_r$=196, which means that CCS fails to reduce the minimum total manpower demand. Note that for all instances, MM_r is smaller than MC_r. Therefore, Scenarios 1 and 6 will not happen in the derived instances, which will be tested later in Section 3.5.6.

Table 3-10. Manpower requirement benchmarks of the instances.

Instance	Manpower requirement benchmarks						
	MS	MC_1	MC_2	MC_3	MC_4	$\sum_{r\in R} MC_r$	MM_r
I1	184	30	40	56	63	189	14
I2	180	29	36	54	63	182	14
I3	196	32	40	58	66	196	15
I4	188	30	39	55	65	189	14
I5	217	34	42	66	76	218	17
I6	194	32	35	62	66	195	16
I7	227	36	40	72	79	227	19
I8	218	34	39	69	76	218	18

Table 3-11. Manpower availability levels and corresponding scenarios.

Availability level					Instance - Scenario							
Index	Class 1	Class 2	Class 3	Class 4	I1-M	I2-M	I3-M	I4-M	I5-M	I6-M	I7-M	I8-M
Level 1	36	42	72	79	Scenario 8	Scenario 8	Scenario 8	Scenario 8	Scenario 8	Scenario 8	Scenario 8	Scenario 8
Level 2	29	35	54	63	Scenario 4	Scenario 5	Scenario 3	Scenario 4	Scenario 4	Scenario 4	Scenario 3	Scenario 3
Level 3	41	14	73	70	Scenario 5	Scenario 5	Scenario 7	Scenario 5	Scenario 2	Scenario 7	Scenario 2	Scenario 2

In reality, the cabin crew availability in airlines may vary over time due to vacations, day-offs, medical checks, training or employee turnover. In this study, three cabin crew availability levels are derived to test the performance of the proposed approach based on the obtained benchmarks. Firstly, the maximum value of MC_r for each class among the instances is selected to form Level 1 cabin crew availability (36, 42, 72, and 79 respectively, 229 totally). Secondly, the minimum value of MC_r for each class among the instances is selected to form Level 2 cabin crew availability (29, 35, 54, and 63 respectively, 181 totally). Observing the relationship between the formed availability levels (i.e., Levels 1 and 2) with the obtained manpower requirement benchmarks (as shown in **Table 3-10**), it is found that Scenarios 2 and 7 are not involved. Therefore, Level 3 is randomly generated (41, 14, 73, and 70 respectively, 198 totally)[15] to derive these two scenarios. Under these three manpower availability levels, various scenarios could be generated with the test instances, indicating the advantages and efficiency of the proposed model.

As discussed in Section 3.3, when the proposed MICCPP-ACCS is applied, the relationship between cabin crew availability levels and manpower requirement benchmarks determines whether there is a shortage in the existing manpower, and whether CCS or extra cabin crews are required to complete the schedule (as explained in Scenario 1 to Scenario 8 in **Table 3-4**). **Table 3-11** summarizes the scenarios corresponding to each generated availability level in each instance. For example, for I1-M under Level 1, the quantity of available cabin crews for each class is larger than MC_r. Therefore, there is no manpower shortage or need for CCS/extra crews, which corresponds to Scenario 8. On the other hand, for I1-M under Level 2, the total availability $TA(181)$ is lower than $MS(184)$, and the quantity of available cabin crews for each class is equal to or smaller than MC_r, which implies a manpower shortage in this case. Moreover, $MS < \sum_{r \in R} MC_r$ holds in I1-M. Therefore, Scenario 4 applies to this case, requiring both CCS and extra manpower to cover all duties. In particular, the total extra manpower demand is $MS - TA = 3$. In I1-M with Level 3, the total availability $TA(198)$ is larger than $MS(184)$, while the availability of Class 2 is lower than MC_2 and equal to MM_2. Accordingly, this situation corresponds to Scenario 5, where only CCS is needed to deal with the manpower shortage. For I3-M, $MS = \sum_{r \in R} MC_r$, which means that CCS fails to reduce the minimum manpower demand. When Level 2 is applied, all classes of available manpower fail to complete their tasks on their own (that is, for all r, $d_r \leq MC_r$). Accordingly, the total number of $\sum_{r \in R}(MC_r - d_r)$ (3, 5, 4, and 3 for each class, totally 15) extra cabin crews are

[15] The manpower availability of each class under Level 3 is randomly generated within the interval of [9, 41], [9, 47], [9, 77], and [9, 84] respectively. In particular, the lower bound (9) is equal to the minimum MM_r among all instances minus 5 (14-5=9), while the upper bound is equal to the maximum MC_r among all instances plus 5 for each class, in order to derive Scenario 2 for some instances ($TA<MS$, while for any r, the availability number is higher than MC_r) and Scenario 7 for some instances ($TA \geqslant MS$, while for any r, the availability number is lower than MM_r).

required, without the requirement for CCS (as Scenario 3). On the other hand, when Level 3 is applied to I3-M, Scenario 7 occurs, with the total availability larger than $MS(196)$, while Class 2 is lower than MM_2. In this situation, both CCS and one Class 2 extra cabin crew ($MM_2 - d_2 = 1$) are demanded. Moreover, let's see I8-M under Level 3 that corresponds to Scenario 2. Herein, the total availability is smaller than $MS(218)$, suggesting a great manpower shortage, although the availability levels for Class 1 and 3 are higher than MC_1 and MC_3 respectively. Besides, the Class 2 availability is lower than MM_2. Consequently, overall 20 extra cabin crews ($\text{Max}\{\sum_{r\in R^*}(MM_r - d_r), (MS - TA)\}$=20) should be employed. More importantly, CCS plays a pivotal role in dealing with the manpower shortage dilemma in this case. The details of all scenarios corresponding to each instance and availability level are illustrated in **Table C-2** in Appendix C.

3.5.4. Demonstration: The Merits of MICCPP-ACCS over TCCPP

To demonstrate the relative advantages of the proposed model, particularly in terms of utilization improvement and cost reduction, the solutions obtained from MICCPP-ACCS and TCCPP (the sum of all five aircraft types) under Level 1, Level 2, and Level 3 for the derived instances are compared. Note that TCCPP ignores the manpower availability limitation, which implies that the solution process under all the three availability levels are identical for each instance. The computation times of MICCPP-ACCS and TCCPP are listed in **Table C-6** and **Table C-7** (in Appendix C), respectively. Specifically, the overall average computation time for each instance (all three availability levels) is 24.193s by MICCPP-ACCS, while the total computation time for all five aircraft types of each instance is 0.333s by TCCPP. It is reasonable to witness the difference in computation time between MICCPP-ACCS and TCCPP, considering the great discrepancy in problem scale and complexity of the two models. The total extra manpower demand under each availability level in TCCPP equals the total manpower demand obtained in the solution minus the availability quantity. On the other hand, as the cabin crew availability constraints are considered in MICCPP-ACCS, MICCPP-ACCS is solved for each instance under each availability level separately. According to the discussion with the managers from The Airways, it is identified that manpower utilization improvement is an important objective for them when conducting cabin crew scheduling. Besides, higher utilization means less manpower waste, which translates into cost reduction. Therefore, manpower utilization is utilized as a criterion to judge the solutions from the perspective of airlines. However, it should be pointed out that higher manpower utilization might not be welcomed by cabin crews due to the associated higher workload and greater fatigue. The manpower utilization is defined as follows:

Utilization=Total effective flight time / Total maximum allowed TAFB of all manpower;

Total effective flight time=$\sum_{i \in F}(\sum_{r \in R} b_i^r$ × flight period).

In the following, the performance of the two models are compared to show the advantageous characteristics of the proposed MICCPP-ACCS over TCCPP. Then, the impact of manpower availability levels on manpower management is discussed by analyzing the outcomes under the three levels of each model. Finally, focusing on Type 5 instances, the results obtained from the two methodologies are measured to illustrate the importance to integrate the flight manpower requirement heterogeneity into the decision framework when constructing pairings for cabin crews.

3.5.4.1. Relative Performance of MICCPP-ACCS Over TCCPP

The solution details of the two models are summarized in **Table C-3** and **Table C-4**, while **Table C-5** represents the relative performance of the two models (see Appendix C). The performance comparisons between the two models are depicted in **Figure 3-5** to **Figure 3-7**, with each under an availability level, revealing the potential merits of the proposed approach in terms of the high manpower utilization and low cost incurred.

The bold solid line represents MICCPP-ACCS while the thin dotted line stands for TCCPP. In each figure, parts (a), (b), (c), and (d) represent the results regarding manpower utilization, associated cost, total manpower used, and extra manpower demand respectively. From these three figures, some managerial remarks could be derived as follows.

Firstly, analyzing parts (a) and (b) of **Figure 3-5** to **Figure 3-7**, it is obvious that the proposed MICCPP-ACCS achieves significant improvement in manpower utilization than TCCPP, by a mean of 199.4%, coupled with a remarkable cost reduction of an average of 61%. The maximum utilization increase even reaches 266.9% in I2 under Level 2 availability and the maximum cost reduction is 66.4% in I1 under Level 3. However, the improvement in manpower utilization inevitably leads to an increase in the average number of flights and duties in a pairing, and the average length of pairing elapsed time. The results show that there are on average 166% more flights, 105.7% more duties, and 183.3% longer elapsed time in the pairings obtained from MICCPP-ACCS than those from TCCPP (see **Table C-5**).

Secondly, examining parts (c) and (d) of **Figure 3-5** to **Figure 3-7**, it is found that with a higher manpower utilization, the proposed MICCPP-ACCS requires much less manpower to complete the flight schedules than TCCPP, which further implies a reduction in the demand for extra cabin crews. Remarkably, the proposed approach averagely achieves 66.3% and 97.9% reduction in total manpower used and extra manpower demand respectively than TCCPP, which proves the higher solution efficiency of the proposed approach. In 12 out of all 24 cases, the requirement for extra manpower is even eliminated in MICCPP-ACCS (e.g., I1 under Level 1).

Thirdly, the obtained TCCPP manpower demand fluctuates much more significantly than that obtained from MICCPP-ACCS. The average standard deviation of the total manpower used across all instances under the three availability levels for TCCPP reaches 40.24, while that for MICCPP-ACCS is only 9.15 (reduced by 77.26%), which proves the lower impact of flight fluctuation on cabin crew management of the proposed approach over TCCPP. Similar conclusions could be drawn when the outcomes in terms of extra manpower demand are examined. Besides, the cost of TCCPP also fluctuates more greatly than that of MICCPP-ACCS.

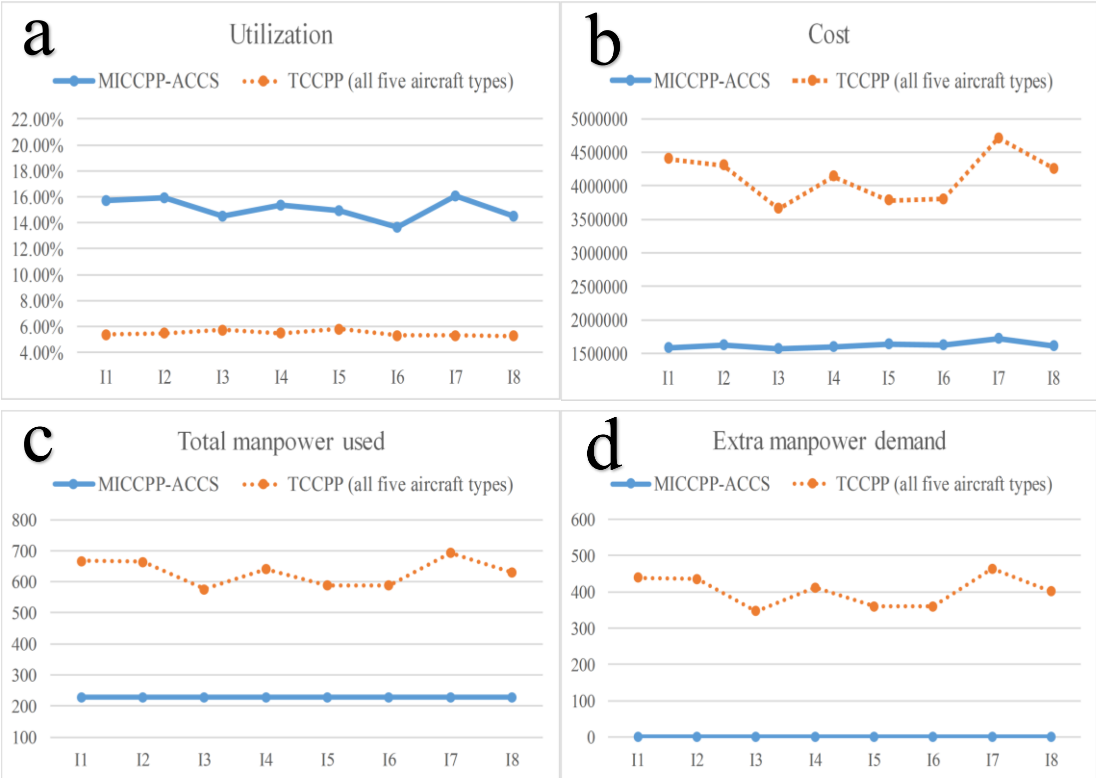

Figure 3-5. The performance comparisons between MICCPP-ACCS and TCCPP (under Level 1).

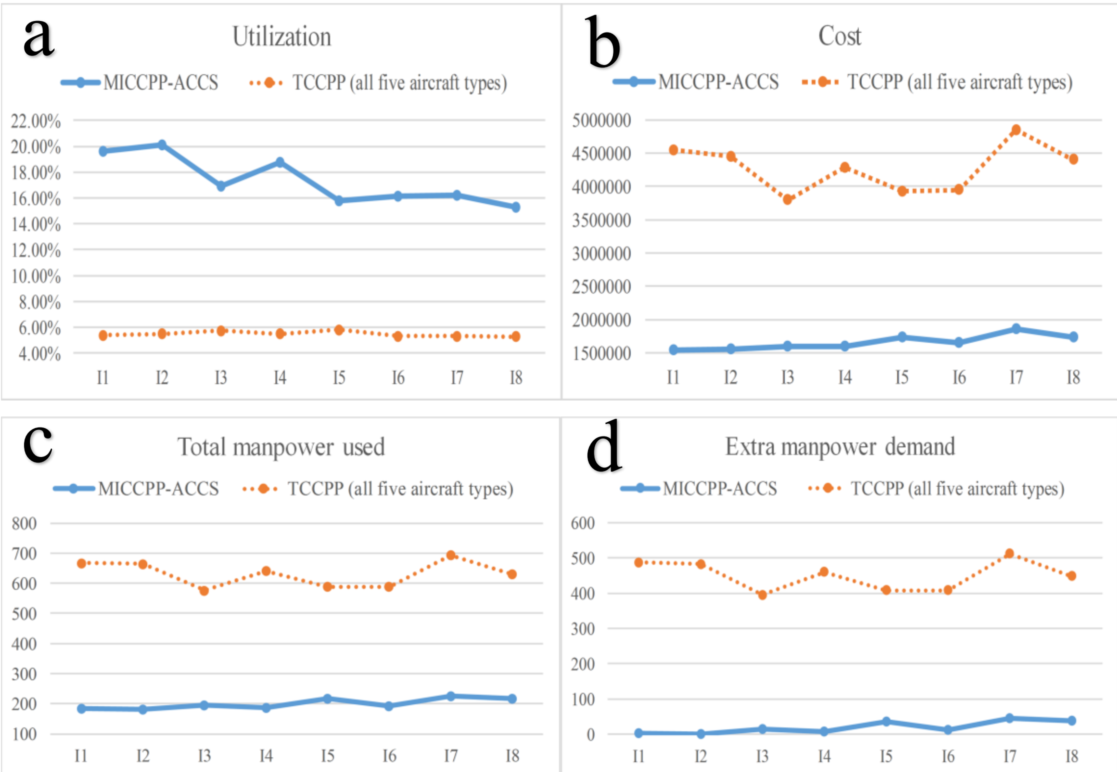

Figure 3-6. The performance comparisons between MICCPP-ACCS and TCCPP (under Level 2).

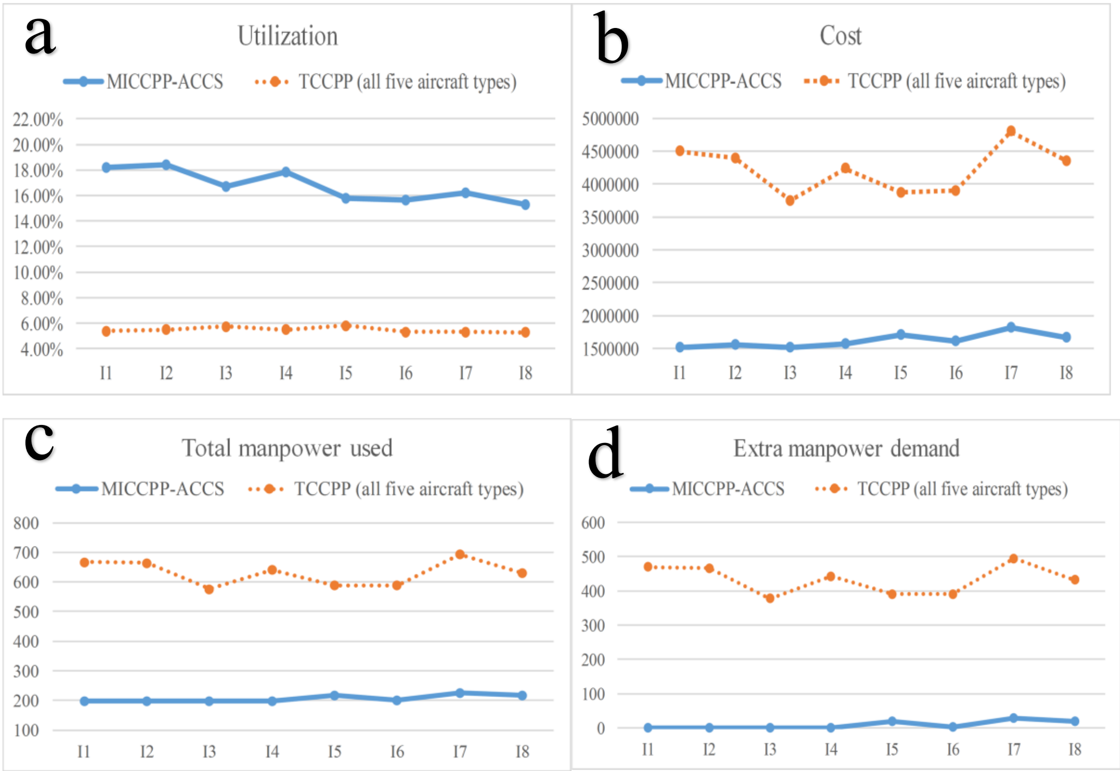

Figure 3-7. The performance comparisons between MICCPP-ACCS and TCCPP (under Level 3).

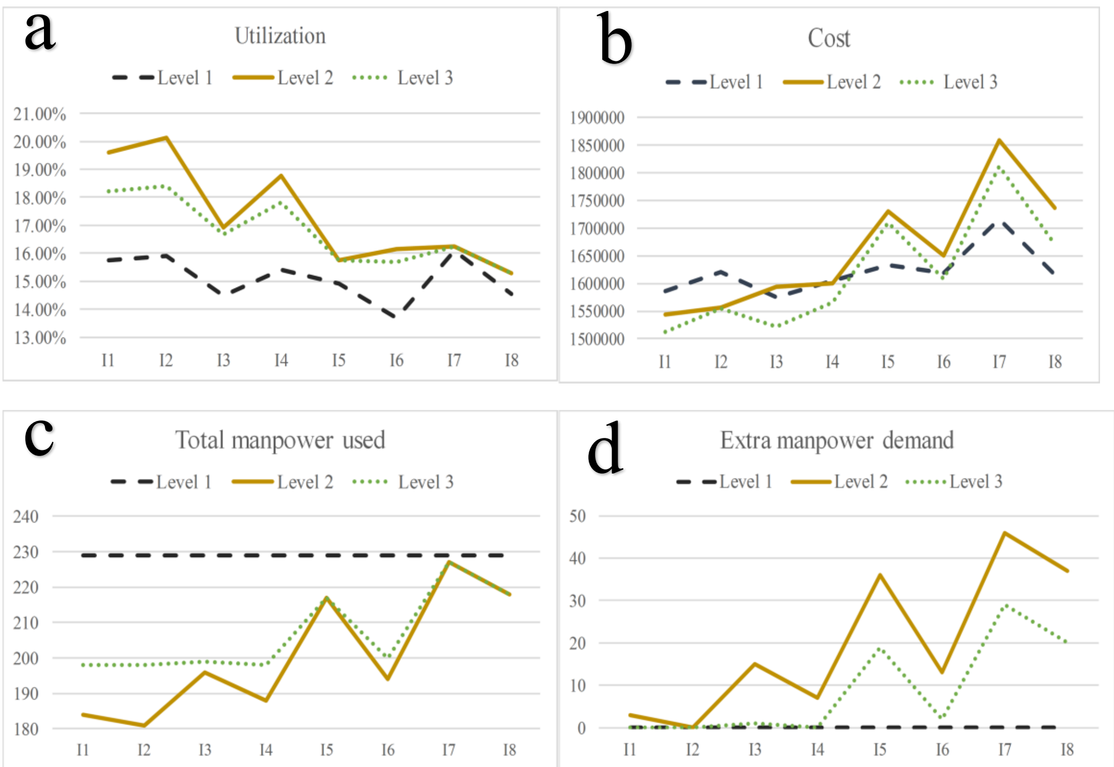

Figure 3-8. The performance comparisons among the three availability levels applying MICCPP-ACCS.

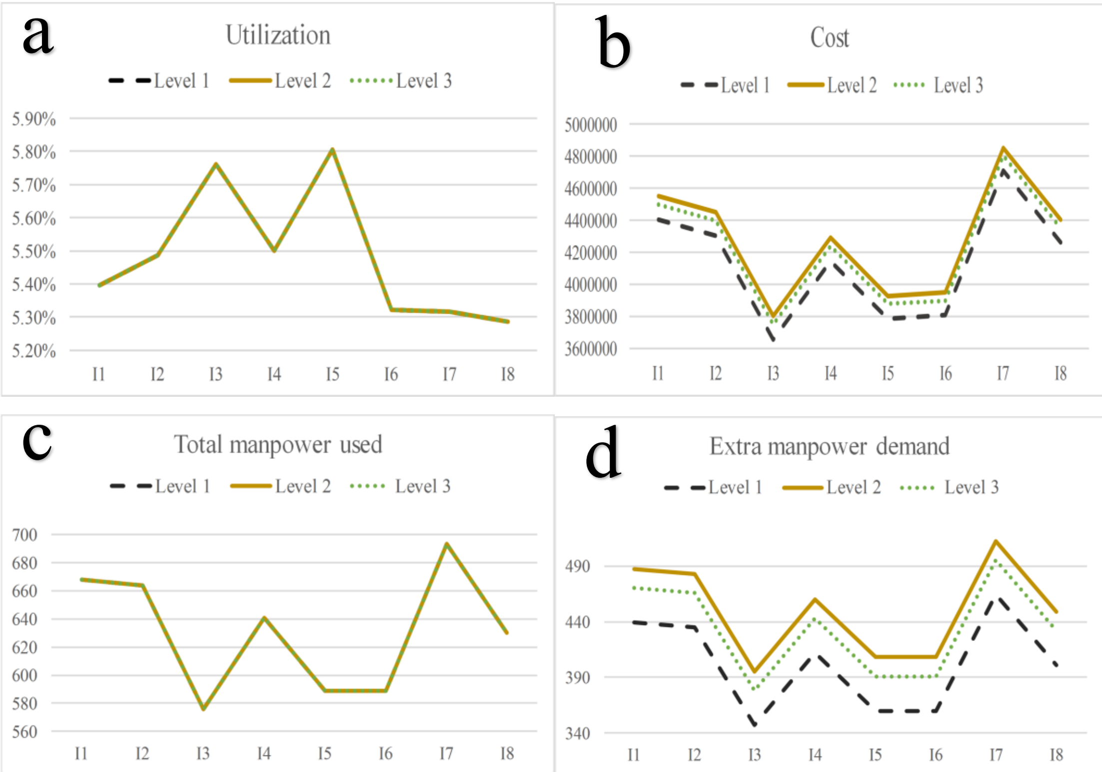

Figure 3-9. The performance comparisons among the three availability levels applying TCCPP.

3.5.4.2. The Effect of Manpower Availability Levels

The solutions obtained from MICCPP-ACCS under the three levels are summarized in **Figure 3-8**, while those from TCCPP are illustrated in **Figure 3-9**. The dashed line, solid line, and dotted line stand for Levels 1, 2, and 3, respectively. From these two figures, the effect of manpower availability levels on cabin crew management could be investigated when the two models are utilized.

Firstly, for MICCPP-ACCS, the cabin crew utilization increases along with the decrease in the availability levels examined. As could be seen in part (a) of **Figure 3-8**, Level 2 with the least available manpower achieves the highest cabin crew utilization, while Level 1 achieves the lowest. However, the realized manpower utilization for TCCPP under the three availability levels are identical (part (a) of **Figure 3-9**). This is primarily because the proposed MICCPP-ACCS has the ability to identify feasible solutions that guarantee the flight schedule to be fully served using available manpower as much as possible before hiring extra cabin crews, thus raising manpower utilization when the availability level is low, while TCCPP is not equipped with this function.

Secondly, based on the discussions above regarding the variation of manpower utilization along with availability levels, one could expect that the availability level with the lowest utilization (Level 1) should apply the most cabin crews while the level with the highest utilization (Level 2) shall use the least manpower to serve the flights in MICCPP-ACCS. Part (c) in **Figure 3-8** verifies this expectation. Actually, as the available manpower under Level 1 is larger than the minimum total manpower demand (TA>MS) for all instances, there is no need for extra cabin crews, making the dashed line in part (c) of **Figure 3-8** a straight line equal to 229 (the sum of available manpower under Level 1) and that in part (d) equal to 0. However, manpower insufficiency occurs in some instances under Level 2 and Level 3, which leads to demands for extra manpower, causing the solid and dotted lines in part (c) and (d) curves. Specifically, Level 2 with the least available manpower requires the most extra cabin crews. Differently, the manpower availability level imposes no influence on the total manpower requirement for TCCPP, and it only affects the extra manpower demand.

Thirdly, it is observed that the impact of flight fluctuation on cabin crew management could be affected by the manpower availability levels in MICCPP-ACCS, while could not in TCCPP. When comparing the two "part (c)" in **Figure 3-8** and **Figure 3-9**, it is seen that the total number of cabin crews used obtained from TCCPP always fluctuates along with flight fluctuation, regardless of the manpower availability levels. On the contrast, for MICCPP-ACCS, the flight fluctuation imposes less or even no impact on cabin crew management. For example, under Level 1, the available manpower has the ability to deal with any change in the tested flight schedules without facing the trouble of manpower shortage, thus eliminating the influence of flight fluctuation.

Lastly, the cost curves obtained under the three availability levels have the same shape in TCCPP, while those in MICCPP-ACCS have more complicated structures. For each instance of TCCPP, the TAFB cost remains unchanged regardless of the availability levels. The only difference in the total costs among the three levels is about the fixed payment for manpower. For Level 1, although the fixed payment cost for the available manpower is the highest among the three levels, the total cost is the lowest due to the minimum extra cabin crew employment. Oppositely, Level 2 encounters the highest total cost owing to the intensive extra manpower fixed payment (part (b) of **Figure 3-9**). However, the TAFB cost varies according to the manpower availability levels in MICCPP-ACCS. In general, the TAFB cost under Level 1 is the lowest in each instance among the three levels because better (cost-effective) combinations of pairings could be found using more available manpower. However, due to the fixed payments for both available and extra manpower, there are various relationships among the costs of the three levels. For example, in I1, Level 1 derives the most expensive cost among all levels due to the costly fixed payment for available cabin crews despite its lowest TAFB cost. However, in I8, the overall expenditure under Level 1 becomes the smallest due to the avoidance of extra manpower employment.

3.5.4.3. The Impact of Flight Manpower Requirement Heterogeneity

To highlight the importance of considering the flight manpower requirement heterogeneity when building pairings for cabin crews, the results obtained from MICCPP-ACCS and TCCPP are compared based on Type 5 instances (involving two cabin layouts, thus leading to heterogeneous flight manpower requirements). The Type 5 MICCPP-ACCS is denoted as Ix-M-T5. The availability level applied here consists of the minimum MC_r for each class among the Type 5 instances (12, 16, 13, and 17 respectively (Level 4)). The relative performance is shown in **Table 3-12**. Apparently, even within the same type of aircraft, the manpower requirement heterogeneity caused by different cabin layouts leads to low manpower utilization and high costs for TCCPP. On average, MICCPP-ACCS achieves 124.3% improvement in manpower utilization and 45.4% reduction in costs than TCCPP, which proves the necessity and importance to integrate the consideration of flight manpower requirement heterogeneity into the decision framework during the cabin crew pairing problem.

Table 3-12. Relative performance of MICCPP-ACCS over TCCPP for Type 5 instances under Level 4.

Index	Reduction			Utilization improvement
	Total manpower used	Extra manpower used	Cost	
I1-M-T5 / I1-T5	66.0%	82.8%	57.4%	193.8%
I2-M-T5 / I2-T5	67.8%	87.8%	57.3%	211.0%
I3-M-T5 / I3-T5	47.2%	73.3%	36.8%	89.5%
I4-M-T5 / I4-T5	43.4%	82.8%	40.0%	76.8%
I5-M-T5 / I5-T5	43.9%	95.9%	38.5%	78.3%
I6-M-T5 / I6-T5	48.1%	85.3%	40.6%	92.8%
I7-M-T5 / I7-T5	64.7%	86.2%	53.3%	182.9%
I8-M-T5 / I8-T5	40.8%	79.0%	39.6%	69.0%
Average	52.8%	84.2%	**45.4%**	**124.3%**

At last, the reasons for the large deviation in the performances of MICCPP-ACCS and TCCPP (e.g., manpower utilization, average number of flights per pairing, extra manpower demand) are highlighted, with the aim of further emphasizing the importance to consider manpower availability limitation and flight requirement heterogeneity, and to model cabin crews individually for the cabin CPP. It should be noted that this deviation will decrease when the available manpower becomes increasingly sufficient.

First of all, these two approaches have different objectives and constraints. Specifically, TCCPP aims to identify a minimum-cost set of team pairings that cover each flight at least once, while MICCPP-ACCS aims to identify a minimum-cost set of individual pairings using the available manpower to satisfy the heterogeneous requirements of flights. Accordingly, in the objective function of TCCPP, only the total TAFB cost for the team pairings is considered, while the number of pairings used is not restricted. On the other hand, MICCPP-ACCS tries to fulfill the flight requirements using the available manpower as much as possible. Therefore, in MICCPP-ACCS, cabin crews are required to fly more flights, especially when manpower availability becomes increasingly insufficient. Accordingly, it is reasonable that the individual pairings obtained from MICCPP-ACCS have higher density (e.g., the number of flights per pairing) than the team pairings obtained from TCCPP. After the team pairings are generated, airlines have to assign cabin crews to form each obtained team pairing. As the team pairings have low density, the assigned cabin crews then have low workload, which causes low manpower utilization.

Second, for the team pairings generated by TCCPP, the flight manpower requirement heterogeneity makes the problem of low manpower utilization even worse. Due to the fact that flights require heterogeneous cabin crew configurations, the actual demand for each class of cabin crew for such teams are calculated based on the maximum requirement of the flights on those team pairings, which causes manpower wastes in the flights with less requirements. This manpower waste effect is common across all the four classes of cabin crews when using the team-based pairing approach. However, through the individual scheduling approach, the specific requirements for each class of cabin crew of each flight can be considered and satisfied, which greatly reduces manpower waste.

Third, MICCPP-ACCS applies the CCS strategy that further improves manpower utilization.

3.5.5. Demonstration: The Effect of CCS

This part demonstrates the effect of CCS on improving cabin crew utilization to hedge against the variation in manpower demand during flight fluctuation, by comparing the results obtained from MICCPP-ACCS with those from the simplified MICCPP-A (all four cabin classes). As CCS only allows manpower substitution when certain classes are in a shortage, only Level 2 and Level 3 are considered in this part.

The relative performances of the two models are concluded in **Table 3-13**. The 4th -7th and 10th -13th columns in the table show the information in terms of the CCS solutions obtained from MICCPP-ACCS under the two availability levels, respectively, while the 2nd and 3rd, and 8th and 9th columns show the extra manpower demand reduction and manpower utilization improvement for MICCPP-ACCS over MICCPP-

A under the two availability levels respectively. The number in the 4^{th} -7^{th} and 10^{th} -13^{th} columns represents the times that this class of cabin crews being substituted by other colleagues, while the flights in the brackets explain where the CCS occurs. For example, I4 under Level 2 corresponds to Scenario 4, where $TA\ (181) < MS(188)$, and $d_r < MC_r$ for each r. Besides, $MS\ (188) < \sum_{r \in R} MC_r\ (189)$. Therefore, totally $MS - TA\ (7)$ extra cabin crews shall be employed, coupled with the application of CCS to fulfill the flight schedule. In the solution obtained, $MC_2 - d_2$ (4) extra Class 2 cabin crews, $MC_3 - d_3$ (1) extra Class 3 cabin crews, $MC_4 - d_4$ (2) extra Class 4 cabin crews are employed, while a job of Class 1 is substituted by a Class 4 colleague on Flight 13. However, in the model of MICCPP-A without the function of CCS (under Level 2), the job of Class 1 on Flight 13 could not be substituted by others, thus leading to the employment of an extra Class 1 cabin crew to finish the work. Accordingly, totally eight ($\sum_{r=1,2,3,4}(MC_r - d_r) = 8$) extra cabin crews are required. Consequently, CCS achieves 12.5% reduction in extra manpower demand and 0.5% growth in manpower utilization compared with the situation where CCS is not applied.

It can be seen that for both availability levels (Level 2, Level 3), MICCPP-ACCS averagely performs better than MICCPP-A in terms of manpower utilization and extra manpower demand. However, the degree of the performance improvement is different between the two levels. Under Level 3, MICCPP-ACCS improves manpower utilization by 9.2% and reduces extra manpower demand by 72.9% over MICCPP-A on average, while the figures are only 0.6% and 23.1%, respectively under Level 2. This is actually determined by the relationship between the availability levels with manpower requirement benchmarks which affects the application of CCS. Take I3 as an example. Under Level 2, no possible CCS could be found (Scenario 3). Therefore, the extra manpower demand and manpower utilization for the two models are the same. However, under Level 3, the total available manpower has the ability to finish all the duties with the assistance of CCS (94 times). Besides, the availability of Class 2 is lower than MM_2, which inevitably needs extra manpower (Scenario 7). Therefore, under Level 3, only $MM_2 - d_2$=1 extra cabin crew is needed in MICCPP-ACCS, while

$MC_2 - d_r$=26 extra cabin crews are needed in MICCPP-A. Accordingly, MICCPP-ACCS reduces 96.15% extra manpower demand and increases utilization by 12.56% compared to MICCPP-A under Level 3. Therefore, the relationship between Level 3 with the flight schedule manpower requirement benchmarks generally facilitates more substitutions than Level 2 in MICCPP-ACCS, which in turn achieves higher cabin crew utilization improvement and greater reduction in extra manpower demand than MICCPP-A. This alleviates the impact of manpower variation on cabin crew management to a higher degree.

Table 3-13. Relative performance of MICCPP-ACCS over MICCPP-A (all four cabin classes).

Instance	Level 2						Level 3					
	Extra manpower demand reduction	Utilization improvement	CCS details (Class)				Extra manpower demand reduction	Utilization improvement	CCS details# (Class)			
			1	2	3	4			1	2	3	4
I1	62.5%	2.7%	1 (F83*)	2 (F73)	2 (F0, 13)	0	100.0%	13.1%	0	115	0	0
I2	100.0%	0.6%	0	1 (F84)	1 (F81)	0	100.0%	11.1%	0	126	0	0
I3	0.0%	0.0%	0	0	0	0	96.2%	12.6%	0	94	0	0
I4	12.5%	0.5%	1 (F13)	0	0	0	100.0%	12.6%	0	109	0	0
I5	2.7%	0.5%	0	1 (F53)	3	0	44.1%	6.9%	0	11	0	6
I6	7.1%	0.5%	2	0	1 (F75)	0	90.5%	9.5%	0	70	0	0
I7	0.0%	0.0%	0	0	0	0	17.1%	2.6%	0	0	0	7
I8	0.0%	0.0%	0	0	0	0	35.5%	5.1%	0	5	0	6
Average	23.1%	0.6%					72.9%	9.2%				

*The flights in each instance are numbered chronologically from zero.

#The substitution details under Level 3 are not shown for brevity.

3.5.6. Special Scenarios

Observe that for each class, MM_r is smaller than MC_r in the derived instances. In order to test the special Scenarios 1 and 6 where $MM_r = MC_r$ for the considered classes, a set of semi-artificial instances is constructed by modifying all flight manpower requirements of each class to one for the originally derived instances. The semi-artificial instances are denoted by A-Ix. In the second and fourth columns of **Table 3-14**, all MC_r equal MM_r for each semi-artificial instance. The cabin crew availability is set as 18, 13, 14, and 15 (Level 5, $TA = 60$) to form Scenarios 1 and 6. The fifth column in the table concludes the scenario that each semi-artificial instance corresponds to under Level 5. For example, $TA(60)$ is larger than $MS(56)$ in A-I1, while the availability for Class 2 is lower than $MC_2(MM_2)$. Therefore, A-I1 under Level 5 corresponds to Scenario 6. Although there is exceeding manpower in other classes, they could not be used for substitution since $MM_2 = MC_2$. Therefore, one Class 2 extra crew is needed. For A-I5, TA is lower than MS(68), and $d_r < MC_r(MM_r)$ for classes 2, 3, and 4 (Scenario 1). Similarly, although there is an exceeding cabin crew in Class 1 (d_1 =18>MC_1 =17), no substitution will occur due to the equality between MM_r and MC_r for the three classes under "insufficiency". Accordingly, the number of $MM_r - d_r$ extra manpower is necessary for each of the three classes (that is, 4, 3, 2, respectively).

Table 3-14. Special scenarios in MICCPP-ACCS under Level 5.

Instance	MC_r	MS	MM_r	Scenario	Extra manpower used				CCS
					Class 1	Class 2	Class 3	Class 4	
A-I1	14	56	14	6	0	1	0	0	0
A-I2	14	56	14	6	0	1	0	0	0
A-I3	15	60	15	6	0	2	1	0	0
A-I4	14	56	14	6	0	1	0	0	0
A-I5	17	68	17	1	0	4	3	2	0
A-I6	16	64	16	1	0	3	2	1	0
A-I7	19	76	19	3	1	6	5	4	0
A-I8	18	72	18	3	0	5	4	3	0

3.6. Summary

The cabin crew pairing problem is a crucial challenge faced by airlines, but is understudied in the transportation literature compared to the related problem for cockpit crews. Most existing related works treat cabin crews as identical as cockpit crews regardless of the distinctive characteristics and the practical operations of controlled crew substitution of cabin crews, which leads to low manpower utilization and high operating costs. Based on the research gaps and the observed real-world airline operations, this chapter has presented a new approach named MICCPP-ACCS to generate pairings for multi-class cabin crews individually with the aim of overcoming the deficiencies of the existing team-based method, rooted in the distinctive characterization of airline cabin crews and the effect of the strategy of Controlled Crew

Substitution (CCS). The proposed approach takes into account the multiple cabin crew classes, flight manpower requirement heterogeneity, and manpower availability constraint according to airlines practice. The strategy of CCS that seeks the opportunity to identify feasible solutions with the current available manpower, in order to alleviate the impact of manpower shortage disruption on cabin crew management during flight fluctuation, is then formulated. Besides, a simplified version without the function of CCS, named MICCPP-A, is developed to derive managerial insights. A customized column generation approach is developed to solve the large-scale problem. The relationship between cabin crew availability levels with flight schedule manpower requirement benchmarks is analyzed to derive managerial insights regarding cabin crew management on whether the current available manpower is in a shortage and whether CCS or extra manpower is required. Computational experiments are then conducted to obtain mathematical generalizations and insights. Note that although optimization software using flight copies to deal with the problem of flight requirement heterogeneity has been developed for airlines, this approach is in advance of academic publication. As a result, the importance of modelling cabin crews individually and the advantages of the proposed models are demonstrated based on the team-based pairing approach which is widely applied in the literature.

To validate and confirm the superior performance of the proposed MICCPP-ACCS, computational studies based on real-world collected flight schedules of a Hong Kong based major airline are conducted, through which several conclusions could be generated. First, numerically comparing the performance of the proposed approach with that of the existing method reveals the distinctive characteristics and relative advantages of the proposed approach, especially in terms of manpower utilization improvement (199%) and cost reduction (61%), indicating that the proposed approach is practically useful. Specifically, in the tested cases, the proposed approach shows potential to generate higher manpower utilization when the cabin crew availability level is lower. Second, it is observed that the impact of flight fluctuation on manpower demand is much larger in the existing method than in the proposed approach, which implies the low efficiency of the existing method and the distinctive merits of the proposed approach in hedging against manpower demand variation. Third, the comparison between the proposed approach with its simplified version demonstrates the superior efficacy of CCS in dealing with the manpower shortage dilemma during flight fluctuation by further improving manpower utilization. Specifically, the efficiency of CCS depends on the relationship between the manpower availability levels and the flight schedule manpower requirement benchmarks.

In conclusion, the proposed novel cabin crew pairing model not only improves cabin crew utilization and reduces costs, but also clarifies the significance of considering the unique characteristics of cabin crews and the effect of CCS during the pairing generation process, which provides important managerial insights for air passenger logistics operations.

Chapter 4. Risk-averse Pricing Strategies for Cargo Airlines

Chapter 2 has examined the importance of considering risk in air cargo operations management. Motivated by the importance of the air freight transportation industry and the various challenges faced by freight airlines, this chapter analytically studies the pricing decisions of cargo airlines with the consideration of risk-averse behaviors.[16] Specifically, a system consisting of two competing carriers who are risk-averse to profit uncertainties is considered. First, the basic model explores the optimal prices for the carriers under market demand uncertainty, and investigates the impacts of diverse parameters on the equilibrium prices to generate respective managerial insights. Then, the analyses are extended to integrate cost uncertainty into consideration, and the importance of considering this crucial factor for decision making is highlighted.

As will be shown later on in this chapter, a number of major important insights is derived. First, the equilibrium prices for the two competing risk-averse cargo airlines are perfectly symmetric, determined by various critical parameters. Second, it is identified that carriers should consider not only its own risk attitudes and costs, but also the competitor's risk preferences and operating characteristics during decision making when market competition exists. Third, it is found that the impacts of risk attitudes of decision makers on the optimal prices are twofold as follows: (i) A carrier's risk attitude could directly increase the optimal prices for both carriers if its operating cost is sufficiently large in a duopoly market with competition; and (ii) risk behaviors could affect the optimal prices indirectly by characterizing the effects of other crucial parameters (e.g., demand and cost uncertainties, market competition). For instance, it is identified that a carrier is prone to charge a higher price when the market demand is becoming more volatile if its operating cost is sufficiently high and it is very risk-averse

[16] As a remark, most part of this chapter is summarized in Wen, X., Xu, X., Choi, T. M., & Chung, S.-H. (2019). Optimal Pricing Decisions of Competing Air-Cargo-Carrier Systems – Impacts of Risk Aversion, Demand and Cost Uncertainties. *IEEE Transactions on Systems, Man and Cybernetics: Systems*, forthcoming.

relative to its competitor in a duopoly market with competition. On the other hand, if the operating cost becomes increasingly stochastic, a carrier will not increase its price unless the fixed part of its cost is sufficiently low and its relative risk-averse attitude is very high compared to its competitor. Besides, carriers are inclined to raise their prices when the market competition becomes intensified due to the aversion to profit uncertainties. Fourth, it is shown that market situations affect the impacts of diverse critical factors on the optimal prices significantly. For example, results indicate if a carrier dominates the market, the risk attitude of the other carrier then becomes nonsignificant. Moreover, market share is demonstrated to influence the optimal prices differently when demand is deterministic or uncertain and when market competition does or does not exist.

This chapter is organized as below. First, a basic model is built and the mean-variance objectives for two competing risk-averse air cargo carriers under demand uncertainty are constructed in Section 4.1. Next, Section 4.2 derives the equilibrium solutions and managerial insights based on the basic model. Section 4.3 extends the analyses to integrate the factor of cost uncertainties. Finally, Section 4.4 concludes for the work presented in this chapter.

4.1. Basic Model

In the basic model[17,18], an air transport system consisting of two competing risk-averse freight carriers who need to determine their optimal pricing decisions with volatile market demand is considered. The two carriers are denoted by r=1 or 2. Here, the unit operating cost for each carrier is fixed as c_r, while the competition level between the two players is denoted by λ. The uncertain market demand $\tilde{a}$ ($\tilde{a} = a_0 + \varepsilon$) consists of a fixed part a_0 and an uncertain part ε which follows a normal distribution[19] with the mean of zero and the standard deviation of σ (i.e., $\varepsilon \sim N(0, \sigma^2)$). θ is used to

[17] Note that the notations used in Chapter 3 and Chapter 4 are totally independent. For example, the "r" in Chapter 3 stands for cabin crew classes, while it represents carriers in Chapter 4.
[18] All parameters are normalized within [0,1] in the analyses.
[19] Actually, the results will hold for the case when the randomness follows any symmetric distribution with a zero mean.

represent the market share of Carrier 2 which is determined by various factors like reputation, service quality and company size. Accordingly, $1-\theta$ stands for the market share of Carrier 1. Besides, note that θ could also be treated as consumer preference or loyalty. Therefore, it is sensible that θ is usually not affected by prices. The unit price for each carrier is represented by P_r $(r = 1 \text{ or } 2)$. Following the literature in supply chain and logistics management (Liu et al., 2016; Wang et al., 2017; Zheng et al., 2017), the demand functions for the two carriers (D_1, D_2) are modelled as in Eq. (4-1) and Eq. (4-2).

Eq. (4-1) $$D_1 = (1-\theta)\tilde{a} - P_1 + \lambda P_2,$$

Eq. (4-2) $$D_2 = \theta\tilde{a} - P_2 + \lambda P_1.$$

Then, the profits for the two carriers could be expressed in Eq. (4-3) and Eq. (4-4). To be specific, the demand for one carrier is dependent on both its own and competitor's prices.

Eq. (4-3) $$\pi_1 = (P_1 - c_1)[(1-\theta)\tilde{a} - P_1 + \lambda P_2],$$

Eq. (4-4) $$\pi_2 = (P_2 - c_2)(\theta\tilde{a} - P_2 + \lambda P_1).$$

The competition parameter λ actually indicates the impact of the price adjustment of one carrier on its competitor's demand. For example, when the price of Carrier 2 (P_2) increases by one unit, the demand for its competitor (D_1) would increase by λ. Note that this study only considers the situation when the unit price is no smaller than the unit cost, and the demand for each carrier is non-negative (i.e., $P_r \geq c_r$ and $D_r \geq 0$) to assure no lose for the carriers. With Eq. (4-3) and Eq. (4-4), the expected profit functions for the two carriers could be obtained in Eq. (4-5) and Eq. (4-6).

Eq. (4-5) $$E(\pi_1) = (P_1 - c_1)[(1-\theta)\, a_0 - P_1 + \lambda P_2],$$

Eq. (4-6) $$E(\pi_2) = (P_2 - c_2)(\theta a_0 - P_2 + \lambda P_1).$$

Considering that both carriers are risk-averse to profit uncertainties, the mean-variance (MV) theory is adopted to model the risk-averse preference of the decision makers. The objective function for the MV theory is shown in Eq. (4-7), which equals the expected profit minus the variance of profit multiplying the risk sensitivity coefficient (k).

Eq. (4-7) Maximize: $O = E(\pi) - kV(\pi)$.

Therefore, the respective MV objectives for the two carriers are formulated in Eq. (4-8) and Eq. (4-9). Specifically, the risk sensitivity coefficient for Carrier r (k_r) is a risk aversion indicator for Carrier r. The growth of k_r represents the increasing aversion against profit volatilities for the decision maker. When $k_r = 0$, the freight airline is risk-neutral.

Eq. (4-8) $Max\colon O_1 = (P_1 - c_1)[(1-\theta)\,a_0 - P_1 + \lambda P_2] - k_1[(P_1 - c_1)^2(1-\theta)^2\sigma^2]$,

Eq. (4-9) $Max\colon O_2 = (P_2 - c_2)(\theta a_0 - P_2 + \lambda P_1) - k_2(P_2 - c_2)^2\theta^2\sigma^2$.

Besides, it is pointed out that in the problem setting, consumers could place an order to the carriers long before the event date, which enables the carriers to suitably manage the utilization of aircrafts. Therefore, the capacity limitation is not considered in this work. This is commonly observed in the practice. For instance, the Switzerland-based freight forwarder Panalpina is reported to encourage shippers to book their air cargo shipment orders as early as possible before the start of peak seasons to avoid capacity shortages[20]. Besides, many air cargo carriers allow customers to make ordering one month or even months in advance (like UPS and Emirates SkyCargo). On the other hand, in the literature, Wada et al. (2017) consider long-term agreement orders where capacity is allocated in advance. Therefore, the model setting is reasonable in both practice and academics.

4.2. Optimal Decisions: An Equilibrium Analysis

To focus on exploring the impact of the risk-averse behaviours of carriers, in the following analyses, only the cases when both carriers are risk averse (i.e., $k_r > 0$)[21] are considered. The optimal pricing decisions for the two competitors in the basic model

[20] https://www.aircargonews.net/news/freight-forwarder/single-view/news/shippers-warned-to-book-now-or-face-rate-spikes-and-delays-in-busy-peak-for-air-cargo.html (Retrieved in July, 2017).

[21] The case when the carriers are risk neutral can be explored by setting the risk coefficient k_r to be 0.

(P_1^*, P_2^*) could be obtained by solving Eq. (4-8) and Eq. (4-9), which are summarized in Lemma 1. Note that the list of notation used in the analyses is summarized in **Table D-1** (Appendix D**).** Besides, in the analyses, some important relative risk-averse attitude thresholds and cost thresholds are identified, which are listed in **Table D-2** (Appendix D) and **Table D-3** (Appendix D), respectively. Furthermore, all mathematical proofs are relegated to Appendix E.

Lemma 1. *In the basic model with uncertain demand and fixed costs, the MV objective functions for the two competing risk-averse carriers are strictly concave, and the respective optimal prices are given as follows*:

$$P_1^* = \frac{2(1+S_2k_2)[(1-\theta)a_0 + c_1(1+2S_1k_1)] + \lambda[\theta a_0 + c_2(1+2S_2k_2)]}{4(1+S_1k_1)(1+S_2k_2) - \lambda^2},$$

$$P_2^* = \frac{2(1+S_1k_1)[\theta a_0 + c_2(1+2S_2k_2)] + \lambda[(1-\theta)a_0 + c_1(1+2S_1k_1)]}{4(1+S_1k_1)(1+S_2k_2) - \lambda^2}.$$

Using the notation summarized in **Table D-1**, P_1^* and P_2^* can be represented as $P_1^* = \frac{A_2A_3 + \lambda A_4}{A_1A_2 - \lambda^2}$ and $P_2^* = \frac{A_1A_4 + \lambda A_3}{A_1A_2 - \lambda^2}$, respectively. Lemma 1 shows that when a risk-averse freight airline facing market competition tries to maximize its own MV objective under demand uncertainty, an optimal pricing decision exists. Besides, the equilibrium prices for the two carriers are perfectly symmetric. The major parameters, like market share (θ), competitional level (λ) and demand uncertainty (σ), all impose great effects on the optimal solutions for the two players involved. More importantly, it is interesting to note that the risk attitudes of both carriers impose critical influences on the equilibrium prices for each individual participant (that is, P_r^* is determined by both k_1 and k_2). Therefore, the importance of considering not only the carrier's own risk attitude, but also the risk behavior of its competitor in the decision process is highlighted. Next, the impacts of the diverse crucial factors on the equilibrium prices will be investigated sequentially.

Proposition 1. *In the basic model where two risk-averse carriers compete for uncertain demand with fixed costs, it is found that:*

(i) The optimal prices for the two carriers increase with market competition (i.e., $\frac{\partial P_1^*}{\partial \lambda} \geq 0, \frac{\partial P_2^*}{\partial \lambda} \geq 0$*);*

(ii) With market competition ($\lambda > 0$ *), a carrier's optimal price increases with both its own and competitor's operating costs, while the increase is faster with its' own cost than with the competitor's;*

(iii) Without market competition ($\lambda = 0$ *), a carrier's optimal price increases with its own operating cost, but is unrelated to its competitor's operating cost.*

Proposition 1 summarizes the important insights regarding the impacts of market competition and operating costs on the optimal pricing decisions for the risk-averse carriers. From Proposition 1(i), it could be seen that under demand uncertainty, when market competition is becoming more intensified, both two participants intend to increase their prices. The intuition is explained as follows. Considering that the two carriers are risk-averse to profit uncertainties, when the two companies compete against each other more fiercely, the threats of demand shrinkage drive them to raise their prices, with the aim of maintaining profitability in the uncertain market. Therefore, it is implied that the risk attitudes of decision makers are crucial in characterizing the impact of market competition on the equilibrium prices. From Proposition 1(ii), it is reasonable that the carrier will charge a higher price if its own operating cost increases. On the other hand, due to the competition between the two participants, it is interesting to note that the rise in competitor's cost could also drive a carrier to raise its price. This is mainly because the competitor is prone to increase its price according to the growth of its cost to hedge against profit risks, which leaves a room for the carrier to charge a higher price. Consequently, it is identified that the operating costs of both entities are important determinants for risk-averse carriers when they engage in a competition. However, the influencing power of competitor's cost growth on a carrier's price is smaller than that of the company's own cost growth. Naturally, the driving force of competitor's cost growth vanishes if the two players terminate competition, as shown in Proposition 1(iii).

Proposition 2. *In the basic model where two risk-averse carriers compete for uncertain demand with fixed costs, the impacts of risk sensitivity coefficients of carriers (i.e., k_1, k_2) on the optimal prices are diverse as follows:*

(i) With deterministic demand (σ =0), the risk attitudes of the two carriers impose no impact on P_1^* and P_2^*.

(ii) With uncertain demand ($\sigma \neq 0$),

a) Under a duopoly[22] market with carrier competition ($0 < \theta < 1$, $\lambda > 0$):

P_1^* and P_2^* are increasing with the risk sensitivity coefficient of Carrier r (k_r), if c_r is sufficiently large (i.e., $c_r > CT_r$), or decreasing with k_r if c_r is sufficiently small (i.e., $c_r < CT_r$). The threshold CT_r is increasing in c_{3-r}.

b) When there is no competition in the market ($\lambda = 0$):

Carrier r's risk attitude (k_r) would not affect the optimal price of Carrier (3-r). Besides, CT_r is unrelated with c_{3-r}.

c) Under a monopoly market ($\theta = 0$ or 1):

If Carrier r occupies all the market, the other carrier's risk attitude (k_{3-r}) would not affect the optimal prices of both carriers.

Proposition 2 indicates that the impacts of risk attitudes of decision makers on the equilibrium prices depend on market situations. To be specific, whether the market demand is fixed or uncertain, whether market competition exists, and whether the market is monopoly or duopoly, are crucial in determining the role of risk behaviors in decision making. First of all, as all risks are derived from uncertainties, Proposition 2(i) shows that the risk-averse attitudes of the carriers are irrelevant to the optimal pricing decisions when the market demand is deterministic without any uncertainty. On the other hand, with volatile market demand, risk attitudes impact decision making

[22] In the analyses, the market is named as "duopoly" market if $0 < \theta < 1$, or "monopoly" market if $\theta = 0$ or 1. When $\theta = 0$, Carrier 1 is called "dominator", while Carrier 2 becomes "dominator" if $\theta = 1$.

significantly, which is further affected by market segmentation and market competition. Firstly, under a duopoly market ($0 < \theta < 1$), if the two carriers compete for uncertain market ($\lambda > 0$), there exists a critical cost threshold (CT_r) to determine the influence of risk attitudes. Proposition 2(ii)a) establishes the threshold-setting result on whether a carrier becoming more risk-averse leads to a growth or reduction in the optimal prices for both two participants. Specifically, if the operating cost of a carrier is very high ($c_r > CT_r$), when it becomes more risk-averse, both two carriers will raise their equilibrium prices. Intuitively, carriers are prone to charge a higher price when they become more risk-averse. However, due to the competition in the market and uncertainties in demand, a carrier would not increase its price along with risk aversion unless its operating cost is sufficiently high, which creates great challenges for the company to maintain profitability. Observing the growth in the competitor's price, the other carrier in the market will thus follow. On the opposite, if a carrier's cost is very low ($c_r < CT_r$), then the two participants will increase their prices if it becomes less risk-averse. The reason behind is explained as follows. When the operating cost is low enough, the difficulty in achieving a target profit is low. Therefore, a carrier could be more ambitious to make higher profits by increasing its price, especially when it is less risk-averse. After that, the other carrier in the market will react to follow. Regarding the cost threshold CT_r for a carrier, an increase in the competitor's cost will lead to a higher CT_r. That is, with competition, the increase in the competitor's operating cost would make it more difficult for the two carriers to raise their optimal prices when a carrier becomes more risk-averse. Therefore, it is implied that the competitor's cost imposes a moderating effect on the impact of the risk behavior of a carrier on the optimal prices for the two carriers under the influence of market competition. On the other hand, without the driving force of competition ($\lambda = 0$), it is natural that the other carrier's operating cost has no influence on a carrier's own cost threshold, while the optimal price of a carrier is independent from the other carrier's risk behaviors (see Proposition 2(ii)b)). In addition, when one carrier dominates the whole market ($\theta =$

$0 \; or \; 1$), it is reasonable to observe that the impact of the other carrier's risk attitude becomes nonsignificant on the equilibrium decisions for both two participants (as shown in Proposition 2(ii)c)).

In conclusion, Proposition 2 underlines the importance of considering the risk attitudes of decision makers in the optimal pricing decisions when market demand is volatile. Besides, the significant impacts of market competition in determining the role of competitor's risk behaviors and operating costs in the optimal prices of a carrier are highlighted. Furthermore, market segmentation is also shown to be crucial in the impacts of risk attitudes on decision making.

Proposition 3. *In the basic model where two risk-averse carriers compete for uncertain demand with fixed costs, the impacts of market share on the optimal prices are shown as follows:*

(i) With deterministic demand ($\sigma = 0$): Carrier r increases its optimal price according to the expansion of its own market share.

(ii) With uncertain demand ($\sigma \neq 0$), for Carrier r:

a) With market competition ($\lambda > 0$), its optimal price increases (or decreases) along with its own market share if $c_r > DT_r$ (or $c_r < DT_r$). Besides, DT_r *is positively related to* c_{3-r}.

b) With market competition ($\lambda > 0$), its optimal price increases (or decreases) along with its competitor's market share if $c_{3-r} > ET_{3-r}$ (or $c_{3-r} < ET_{3-r}$). Besides, ET_{3-r} is positively related to c_r.

c) Without market competition (λ=0), its optimal price increases along with its own market share.

Proposition 3 demonstrates the various influences of market share on carriers' optimal pricing decisions. First, as shown in Proposition 3(i), when there is no uncertainty in the market threatening decision makers, carriers will increase their prices to improve profitability according to the expansion of its own market share. However, Proposition 3(ii) indicates that the impacts of market share under demand uncertainty are much different, which is further affected by market competition. Specifically, under competition, a carrier is prone to charge a higher (or lower) price along with the increase of its own market share if its own cost is high (or low) enough (see Proposition 3(ii)a)). The principle behind is explained as follows. The risk of profit volatilities (due to the competition and demand uncertainty in the market) would prevent a carrier from increasing its price when it occupies a larger market unless its operating cost is too high to achieve a targeted profitability level. The threshold DT_r is positively related to the competitor's cost. Therefore, one could expect that when a carrier's own cost is becoming increasingly high while the competitor's cost is becoming increasingly low, the carrier will be easier to raise its price along with the expansion of its market size. On the other hand, when the operating cost is sufficiently low, in order to compete with its competitor for uncertain demand, it is optimal for a carrier to decline its price to attract more consumers when its market share is expanded. In this case, the carrier could maintain a certain profitability level owing to the low cost and expanded market share. Interestingly, this strategy is easier to operate when the competitor's cost becomes higher (which means DT_r becomes higher, and $c_r < DT_r$ becomes easier). Regarding the impact of competitor's market share, critical thresholds for competitor's operating cost (i.e., ET_{3-r}) also exist, as indicated in Proposition 3(ii)b). To be specific, Carrier r intends to raise (or reduce) its price when its competitor's market share increases, with the condition that the competitor's operating cost is higher than ET_{3-r} (or lower than ET_{3-r}). The threshold ET_{3-r} is positively related to the carrier's own cost (c_r). Therefore, one could expect that when c_r is very low (that is, $c_{3-r} > ET_{3-r}$ is easier to be satisfied), if the competitor seizes more and more market share, the risk-averse carrier has to rise its price to keep profitability. On the other hand, if the two carriers do not compete, carriers could always promote their profits in the volatile market by increasing prices along with the expansion of market share (as shown in Proposition 3(ii)c)).

As a remark, Proposition 3 highlights the significant effects of demand uncertainty and risk attitudes of decision makers on the impacts of market share on the optimal prices. Besides, the critical role of market competition in risk-averse decision making is further demonstrated.

Next, how demand uncertainty affects risk-averse decision making is explored. Denote τ_r as the *relative risk-averse attitude of Carrier r over its competitor*, which is equal to $\frac{k_r}{k_{3-r}}$. Then, Proposition 4 is obtained as follows.

Proposition 4. *In the basic model where two risk-averse carriers compete for uncertain demand with fixed costs, the impacts of demand uncertainty on the optimal prices are derived as follows:*

(i) Under a duopoly market ($0 < \theta < 1$) with competition ($\lambda > 0$), for Carrier r:

a) If $\tau_r > \Lambda_r$, its optimal price increases with demand uncertainty if $c_r > YT_r$.

b) If $\tau_{3-r} > \Omega_{3-r}$, its optimal price increases with demand uncertainty if $c_{3\text{-}r} > PT_{3-r}$.

(ii) Under a duopoly market ($0 < \theta < 1$) without competition ($\lambda = 0$), for Carrier 1, its optimal price increases with demand uncertainty if $c_1 > a_0(1-\theta)$, while for Carrier 2, its optimal price increases with demand uncertainty if $c_2 > a_0\theta$.

(iii) Under a monopoly market ($\theta = 0$ or 1):

a) With market competition ($\lambda > 0$), when the market is dominated Carrier r, $\frac{\partial P_1^*}{\partial \sigma}$ and $\frac{\partial P_2^*}{\partial \sigma}$ are positive if $c_r > OT_r$.

b) Without market competition ($\lambda = 0$), when the market is dominated by Carrier r, $\frac{\partial P_{3-r}^*}{\partial \sigma} = 0$. Besides, $\frac{\partial P_r^*}{\partial \sigma} > 0$ if $c_r > a_0$.

Proposition 4 shows that the relative risk-averse attitudes and market situations (i.e., market segmentation and competition) play critical roles in determining the impacts of demand uncertainty on the optimal prices. Proposition 4(i) considers a duopoly market shared by two competing carriers ($0 < \theta < 1$, $\lambda > 0$). Specifically, Proposition 4(i)a) indicates that if the operating cost is very large, a carrier would charge a higher price when the market becomes more volatile if its relative risk-averse attitude over its competitor is sufficiently high. A higher relative risk-averse attitude actually implies that a carrier is becoming more risk-averse to profit uncertainties relative to its competitor. Therefore, when a carrier with high relative risk-averse attitude is facing with increasing demand uncertainty, due to the fear of demand losses, it will not raise its price unless it is challenged by a high operating cost. Interestingly, a carrier will also increase its price according to demand uncertainty if both the relative risk-averse attitude and the operating cost of its competitor are sufficiently large (see Proposition 4(i)b)). This is essentially motivated by the competitor's intension to raise price to deal with profit volatilities in a more volatile environment. On the other hand, if there is no competition in the duopoly market, each carrier will increase its price to hedge against the increasing demand volatility if its own operating cost is high enough, while the other carrier's risk attitudes and costs are irrelevant, as shown in Proposition 4(ii). Moreover, Proposition 4(iii) considers a monopoly market where the market is dominated by one player ($\theta = 0\ or\ 1$). First, if competition exists, both two carriers will choose a higher price with the increase of demand uncertainty if the dominator's operating cost is sufficiently large (as shown in Proposition 4(iii)a)). It is intuitive that the dominator will increase its price to withstand the profit risks brought by the increased demand volatility when its operating cost is very high, while the other carrier in the market will act as a follower due to competition. Second, as shown in Proposition 4(iii)b), if there is no market competition, the rise in demand uncertainty will lead the dominator to increase its price if its cost is sufficiently high, which is similar to the situation with market competition. However, the other carrier in the market will keep its price no matter when demand becomes increasingly or decreasingly uncertain, which is different from the situation with market competition.

In short, Proposition 4 indicates that in addition to market competition and market segmentation, the relative risk-averse attitude of the two carriers also plays a pivotal role in characterizing the impacts of demand uncertainty on the optimal prices. Therefore, it is suggested for an air cargo carrier that it is essential to consider not only its own risk behaviors and operating characteristics, but also its competitor's decisions and features for strategic decision making in the uncertain and competitive environment.

Finally, some important relationships between the optimal price (P_r^*) with major coefficients and corresponding conditions identified in the basic model are summarized in **Table 4-1**. This table aims to provide a quick look about the impacts of the diverse crucial parameters on the optimal prices for risk-averse air cargo carriers.

Table 4-1. Important relationships between P_r^* with major parameters.

	A	Conditions	B	Conditions	C	Conditions	D	Conditions	Remarks
λ	↑								
c_r	↑								
c_{3-r}	↑	$\lambda > 0$							
k_r	→	σ=0	↑	$\sigma \neq 0, 0 < \theta < 1$, $\lambda > 0$, $c_r > CT_r$	→	$\sigma \neq 0$, the market is dominated by Carrier (3-*r*)			
k_{3-r}	→	σ=0	↑	$\sigma \neq 0, 0 < \theta < 1$, $\lambda > 0$, $c_{3-r} > CT_{3-r}$	→	$\sigma \neq 0$, the market is dominated by Carrier *r*	→	$\sigma \neq 0, \lambda = 0$	
θ (1- θ)	↑	$\sigma = 0$	↑	$\sigma \neq 0, \lambda > 0$, $c_r > DT_r$	↑	$\sigma \neq 0, \lambda > 0$, $c_{3-r} < ET_{3-r}$	↑	$\sigma \neq 0, \lambda = 0$	For Carrier 2 (Carrier 1)
σ	↑	$0 < \theta < 1$, $\lambda > 0$, $\tau_r > \Lambda_r$, $c_r > YT_r$	↑	$0 < \theta < 1$, $\lambda > 0$, $\tau_{3-r} > \Omega_{3-r}$, $c_{3-r} > PT_{3-r}$	↑	$\lambda > 0$, $c_r > OT_r$, the market is dominated by Carrier *r*			

4.3. Extended Analyses: Uncertain Costs

As discussed in the introduction, cost uncertainty is a crucial and challenging problem which significantly affects the profitability and development of air cargo carriers. Therefore, after evaluating the pricing decisions under uncertain demand, in this sub-chapter, the basic model is extended to the case when the operating cost is stochastic, to study the impact of cost uncertainty on the optimal pricing decisions. Here, the air freight carriers are facing with uncertain unit costs, $\widetilde{c_r}(\widetilde{c_r} = c_{r0} + \varphi)$. $\widetilde{c_r}$ consists of a fixed part c_{r0} and an uncertain part φ which follows a normal distribution with the mean of zero and standard deviation of δ ($\varphi \sim N(0, \delta^2)$). It is reasonable that the two carriers face the same cost uncertainty as it is derived from fuel price fluctuation. Besides, the unit price for the carriers in the extended model is denoted as P_r^e. Therefore, the updated profit functions for the two players could be formulated as in Eq. (4-10) and Eq. (4-11). The updated expected profits are then shown in Eq. (4-12) and Eq. (4-13), while the corresponding variances of profits are illustrated in Eq. (4-14) and Eq. (4-15).

Eq. (4-10) $\pi_1^e = (P_1^e - \widetilde{c_1})[(1-\theta)\tilde{a} - P_1^e + \lambda P_2^e]$,

Eq. (4-11) $\pi_2^e = (P_2^e - \widetilde{c_2})(\theta\tilde{a} - P_2^e + \lambda P_1^e)$.

Eq. (4-12) $E(\pi_1^e) = (P_1^e - c_{10})[(1-\theta)\, a_0 - P_1^e + \lambda P_2^e]$,

Eq. (4-13) $E(\pi_2^e) = (P_2^e - c_{20})(\theta a_0 - P_2^e + \lambda P_1^e)$.

Eq. (4-14) $V(\pi_1^e) = (1-\theta)^2\sigma^2[\delta^2 + (P_1^e - c_{10})^2] + \delta^2[(1-\theta)\, a_0 - P_1^e + \lambda P_2^e]^2$,

Eq. (4-15) $V(\pi_2^e) = \theta^2\sigma^2[\delta^2 + (P_2^e - c_{20})^2] + \delta^2(\theta a_0 - P_2^e + \lambda P_1^e)^2$.

Similarly, the MV theory is applied to measure the impact of risk-averse attitudes on pricing decisions with the influence of cost uncertainty. The MV objective function for the extended model is constructed in Eq. (4-16).

Eq. (4-16) Maximize: $O_r^e = E(\pi_r^e) - k_r V(\pi_r^e)$. ($r$=1,2)

Solving Eq. (4-16), the optimal pricing decisions for the two risk-averse competing carriers under demand and cost uncertainties (i.e., P_1^{e*} and P_2^{e*}) could be obtained, which are summarized in Lemma 2.

Lemma 2. *In the extended model with uncertain demand and uncertain costs, the MV objective functions for the two competing risk-averse carriers are strictly concave, and the respective optimal prices are given as follows*:

$$P_1^{e*} = \frac{2(1+S_2k_2+k_2\delta^2)[(1-\theta)a_0(1+2k_1\delta^2)+c_{10}(1+2S_1k_1)]+\lambda(1+2k_1\delta^2)[\theta a_0(1+2k_2\delta^2)+c_{20}(1+2S_2k_2)]}{4(1+S_1k_1+k_1\delta^2)(1+S_2k_2+k_2\delta^2)-\lambda^2(1+2k_1\delta^2)(1+2k_2\delta^2)},$$

$$P_2^{e*} = \frac{2(1+S_1k_1+k_1\delta^2)[\theta a_0(1+2k_2\delta^2)+c_{20}(1+2S_2k_2)]+\lambda(1+2k_2\delta^2)[(1-\theta)a_0(1+2k_1\delta^2)+c_{10}(1+2S_1k_1)]}{4(1+S_1k_1+k_1\delta^2)(1+S_2k_2+k_2\delta^2)-\lambda^2(1+2k_1\delta^2)(1+2k_2\delta^2)}.$$

Similar to the basic model, Lemma 2 shows that optimal pricing decisions exist for air cargo carriers to maximize the MV objectives when they face stochastic costs. Besides, the equilibrium prices for the two risk-averse carriers are perfectly symmetric in the extended model. In addition to the major parameters like market share (θ), market competition (λ), market uncertainty (σ), and risk attitudes of the two players (k_r), it is important to note that cost uncertainty (δ) also plays an important role in determining the optimal prices. In the expressions, $\eta_r = 1+2k_r\delta^2$ is defined as the *cost uncertainty risk coefficient*, which reflects the integrated impact of cost uncertainty and risk aversion on the optimal decision making. Applying the notation listed in **Table D-1** (Appendix D), P_1^{e*} and P_2^{e*} could be represented as $P_1^{e*} = \frac{B_2B_3+\lambda\eta_1B_4}{B_1B_2-\lambda^2\eta_1\eta_2}$ and $P_2^{e*} = \frac{B_1B_4+\lambda\eta_2B_3}{B_1B_2-\lambda^2\eta_1\eta_2}$, respectively. Obviously, P_r^{e*} and P_r^* have similar forms expect that P_r^{e*} is featured with the cost uncertainty risk coefficient η_r. Next, Proposition 5 demonstrates the specific impacts of cost uncertainty on the equilibrium prices under different scenarios.

Proposition 5. *In the extended model where two risk-averse carriers facing stochastic costs compete for uncertain demand, the impacts of cost uncertainty on the optimal prices are diverse as follows:*

(i) With market competition ($\lambda > 0$), for Carrier r:

a) If $\tau_r > \vartheta_r$, its optimal price increases with cost uncertainty if $c_{r0} < WT_r$.

b) If $\tau_{3-r} > \varsigma_{3-r}$, its optimal price increases with cost uncertainty if $c_{(3-r)0} < UT_{3-r}$.

(ii) Without market competition ($\lambda = 0$):

a) Under a duopoly market ($0 < \theta < 1$), for Carrier 1, its optimal price increases with cost uncertainty if $c_{10} < (1-\theta)a_0$, while for Carrier 2, its optimal price increases with cost uncertainty if $c_{20} < \theta a_0$.

b) *Under a monopoly market ($\theta = 0$ or 1), when the market is dominated by Carrier r,* $\frac{\partial P_{3-r}^{e\ *}}{\partial \delta} \leq 0$. *Besides,* $\frac{\partial P_r^{e*}}{\partial \delta} > 0$ *if* $c_{r0} < a_0$.

From Proposition 5, it could be seen that the role of cost uncertainty depends on market conditions such as market competition and segmentation. Besides, the relative risk-averse attitude (τ_r) also serves as an important indicator to determine the effect of cost uncertainty, which is similar to the effect of demand uncertainty as discussed in Proposition 4. First of all, with market competition, Proposition 5(i)a) shows that an increase in cost uncertainty would lead to a growth in the optimal price if the fixed part of a carrier's cost (c_{r0}) is low enough ($c_{r0} < WT_r$) and its relative risk-averse attitude over its competitor is high enough. Intuitively, a carrier will charge a higher price to hedge against the increased uncertainty in its operating cost. However, due to demand uncertainty and market competition, a rise in price may result in a reduction in consumer demand. Therefore, for a carrier who is very averse to profit uncertainties relative to its competitor, it will not rise its price when its cost is becoming increasingly stochastic unless the fixed part of its cost could be controlled in a low level (i.e., $c_{r0} < WT_r$). Besides, a carrier would also increase its price along with cost uncertainty if its competitor's relative risk-averse attitude is very high and the competitor's cost (fixed part) is very low (see Proposition 5(i)b)). The motivation is the competitor's proneness to deal with the profit risks caused by the increased cost uncertainty through raising price. On the other hand, if the two participants do not compete ($\lambda = 0$), the influence of cost uncertainty on a carrier's optimal prices further depends on market segmentation, while the operating characteristics of the other carrier in the market becomes irrelevant. Specifically, if the market is a duopoly market (see Proposition 5(ii)a)), the optimal price of a carrier would be positively related to cost uncertainty if the fixed part of its cost is low enough. The intuition is that only when the fixed component of cost is sufficiently low, will it be possible for the carrier to maintain profitability after increasing price (demand decreases accordingly) to deal with the increased cost uncertainty. Similarly, Carrier r will raise its price along with cost uncertainty if $c_{r0} < a_0$ when the market is dominated by Carrier r (in Proposition 5(ii)b)). However, in the monopoly market, the other carrier has to decrease its price when the operating cost becomes more stochastic to keep profitability.

In short, Proposition 5 derives insights regarding the impacts of cost uncertainty on the optimal pricing decisions for risk-averse air cargo carriers under a competitive and uncertain market environment. Considering the highly volatile crude oil market and the significant fuel price fluctuation in the modern world, it is believed that the extended analyses in this sub-chapter could provide useful implications and guidelines for both practitioners and academics on the strategies to deal with the challenges arising from air freight operating costs.

4.4. Summary

Nowadays, air freight transportation is becoming increasingly important for global logistics systems to facilitate quick and reliable logistics services. However, despite the fast growth, the industry is challenged by intensive market competition and highly volatile consumer demand. Besides, airlines are also facing with significant operating cost uncertainty caused by jet-fuel price fluctuation. As a result, in order to enhance their survivability and profitability in the highly competitive and stochastic market environment, many air cargo carriers become conservative and behave as risk-averse in decision making. Among the strategic decisions of cargo airlines, the optimal pricing problem is the most crucial but challenging one, which significantly impacts the development of air cargo carriers. However, although the importance of pricing decisions with risk considerations has been realized, the optimal pricing decisions for risk-averse air cargo carriers in the presence of cost and demand uncertainties are still under-investigated. This thesis thus aims to examine the impacts of risk attitudes of decision makers, market competition, demand uncertainty and cost uncertainty on the optimal pricing decisions for air cargo logistics by applying the MV theory.

In this chapter, through analytically exploring a basic model where two risk-averse air cargo carriers with deterministic operating costs compete for uncertain demand and an extended model where both demand and cost are uncertain, the equilibrium prices for the two carriers and the impacts of diverse crucial parameters on the optimal decision making have been explored. The analytical results have generated the following major findings and insights. First, the optimal prices and important thresholds for the two carriers are perfectly symmetric either in the basic or the extended model. Second, the optimal price of a carrier is affected not only by its own risk attitudes and costs, but also by the competitor's characteristics (e.g., costs, risk preferences) if they engage in a competition. Otherwise, without competition, the decisions of the two carriers are irrelevant. Third, the risk-averse behaviors of carrier managers could affect the optimal prices either directly or indirectly. For instance, if a carrier's cost is high enough, its increasing risk-averse attitude could directly lead to a growth in the optimal prices for the two participants in a duopoly market with competition. On the other hand, the risk-averse behaviors could impose indirect impacts on the optimal prices through affecting the effects of other important parameters. For example, results show that the risk-averse attitude prevents a carrier who faces uncertain demand and market competition from raising its price according to the expansion of market share except that its operating cost is sufficiently large. More importantly, the relative risk-averse attitudes of the two carriers are demonstrated to be crucial in evaluating the impacts of both demand and cost uncertainties on the optimal decision making. Fourth, the market situations are critical determinants in the risk-averse pricing decisions. For example, when the two carriers compete more fiercely, both two players will increase their prices. Besides, market segmentation (i.e., whether the market is duopoly or monopoly) imposes great impacts on the effects of risk sensitivity coefficients, demand uncertainty and cost uncertainty. For instance, if the market is dominated by a carrier without competition, then the risk attitude of the other carrier becomes insignificant. Besides, the other carrier's optimal price is irrelevant to demand uncertainty (or negatively related to cost uncertainty), while the dominator's optimal price is positively related to demand uncertainty (or cost uncertainty) if the dominator's cost is sufficiently high (or low).

To conclude, the research presented in this chapter contributes to the existing literature of systems engineering and science by integrating risk considerations, market competition and market uncertainties (demand and cost) into the optimal pricing decisions for air cargo carriers. The equilibrium solutions and how the crucial factors impact the optimal prices have been explored. Through comprehensive investigation, the importance to enhance pricing decisions for air cargo logistics operators by considering these critical factors in the current highly volatile and competitive market has been highlighted.

Chapter 5. Concluding Remarks and Future Studies

5.1. Conclusions

This thesis focuses on enhancing the decision making for air logistics operations from two aspects: cabin crew scheduling for air passenger logistics, and risk analysis for air cargo logistics. To be specific, considering the importance of cabin crews for air passenger logistics operations, a novel individual pairing approach for airline cabin crews which can significantly increase manpower utilization and reduce operating costs has been developed. Besides, realizing the great challenges of the pricing decisions of freight airlines under the highly volatile market, the pricing strategies have been analytically explored by integrating risk analysis into the decision framework for air cargo logistics operations. The well-established mean-variance theory is utilized to conduct risk analysis in this research.

Chapter 2 has conducted detailed literature review regarding air logistics operations management from both air passenger and air cargo perspectives, and identified critical research gaps for these two domains. Besides, the existing studies with risk analysis have been analyzed, and the importance of integrating risk considerations into the decision framework under uncertainties has been highlighted. Moreover, the application of the mean-variance theory for risk analysis with air logistics has been comprehensively surveyed, which provides solid theoretical support for this research.

Then in Chapter 3, based on the significant research gaps identified regarding the airline cabin crew pairing problem and the observed real-world air passenger logistics practice, a novel individual pairing approach for cabin crews (named *Multi-class individual cabin crew pairing problem with availability and controlled crew substitution* (MICCPP-ACCS)) has been developed to generate pairings for multi-class cabin crews individually with the objective of overcoming the deficiencies of the existing team-based approach. Rooted in the distinctive characterization of airline cabin crews and the effect of the strategy of Controlled Crew Substitution (CCS), the proposed MICCPP-ACCS demonstrates superior performances compared to the existing team-based method, especially in terms of manpower utilization improvement and cost reduction. Besides, the proposed approach shows great potential to generate higher manpower utilization when the cabin crew availability level is lower, while the impact of flight fluctuation on manpower demand is much larger in the existing method than in the proposed approach. Moreover, a *Multi-class individual cabin crew pairing problem with availability* (MICCPP-A) has been constructed which is a simplified version of MICCPP-ACCS without the function of CCS, to derive more managerial insights. Besides, the proposed models have facilitated the analysis on the relationship between manpower availability levels with flight manpower requirement benchmarks to obtain insightful cabin crew planning implications, which can greatly enhance the decision making for air passenger logistics operations.

Afterwards, in Chapter 4, realizing the diverse uncertainties faced by freight airlines and the intensive competition in the market, the important pricing strategies for air cargo logistics operators with the consideration of risk-averse behaviors have been explored. The mean-variance theory is applied to conduct risk analysis, which derives many crucial managerial insights. For example, it has been found that the optimal price of a carrier is affected not only by its own risk attitudes and costs, but also by the competitor's operation characteristics (e.g., costs, risk preferences). Besides, the risk-averse behaviors of carrier managers are demonstrated to affect the optimal prices either directly or indirectly. For instance, if a carrier's cost is high enough, when it becomes more risk-averse, both two companies in a competitive duopoly market would increase their optimal prices. On the other hand, the risk-averse attitude is shown to indirectly prevent a carrier from raising its price according to the expansion of market share, except that its operating cost is sufficiently high. More importantly, the relative risk-averse attitudes of the two carriers in the market are demonstrated to be crucial determinants for the impacts of both demand and cost uncertainties on the optimal pricing decisions. Besides, the market situations (e.g., market segmentation) impact the optimal risk-averse pricing strategies significantly.

In conclusion, this thesis has analytically studied the crucial cabin crew scheduling decisions for air passenger transportation by developing a novel pairing approach, and investigated the important pricing decisions for air cargo transportation through risk analysis, with the objective of enhancing the decision quality for modern air logistics operations.

5.2. Future Studies

In this sub-chapter, several interesting and important future research directions are proposed according to the work done in this doctoral thesis.

Regarding the novel individual cabin crew pairing approach proposed in Chapter 3, the proposed models have encountered several limitations which deserve future research as follows. First of all, as the main focus of this study is enhancing cabin crew pairing decisions from the perspective of airlines (i.e., improving manpower utilization and reducing costs), the psychological factors of cabin crews are ignored in the model setting. From the organizational psychology literature, it is known that colleague support can enhance employees' job performance and work engagement, while familiarity with team members is helpful in improving productivity (Farh et al., 2012; Guzzo & Dickson, 1996). Therefore, although the individual scheduling approach is useful for airlines, it could impair the psychological needs of cabin crews. Hence, a promising future research direction is to consider both the financial cost of airlines and the psychological demands of cabin crews when making pairing decisions for them. It will be interesting to explore the trade-offs between the cost efficiency brought by the individual scheduling approach and the team spirit brought by the team scheduling approach. Moreover, Chapter 3 of this study concentrates on the first stage of crew scheduling problem, i.e., crew pairing problem. Therefore, future research could extend the analysis presented in this study to investigate the following crew assignment problem. Besides, the problem here is considered under deterministic scenarios. It will be interesting to explore the related crew recovery problems under disruption management. Additionally, as discussed, imposing the manpower availability constraint (i.e., an upper limit for the pairings generated) might increase the densities of pairings generated (e.g., the number of flights per pairing), which saves operating costs for airlines. However, this would generate higher workload for cabin crews, causing fatigue and dissatisfaction among employees, which in turn produces negative impact on the airlines performances. Recently, Yildiz et al. (2017) propose to utilize the Three Process Model of Alertness to characterize the fatigue factor of pilots in the related pairing problem, with the multiple objectives of minimizing financial costs and pilot fatigue at the same time. Therefore, one interesting extension of the current study is to pursue a balance between manpower utilization improvement and cabin crew fatigue reduction.

On the other hand, for the optimal pricing strategies of cargo airlines measured by the mean-variance theory which is presented in Chapter 4, more risk measurements like mean-downside risk (MDR) approach (Chan et al., 2018) could be applied to characterize the risk behaviors of air cargo carriers. Besides, the MV theory can also facilitate the profit risk analysis in the research topics like airline alliances and competitions, entry decisions, revenue management, capacity management, and booking control. Moreover, it will be interesting and challenging to apply the MV theory into the airline disruption management problem. In that case, the operations risk cost due to daily disruptions can be measured and discussed in a more theoretical way by including the variance of operations costs into the objective function.

Appendix A. Notation of Parameters and Variables for Chapter 3

Table A-1 summarizes the notation of parameters and variables used in this work.

Table A-1. Notation of parameters and variables used in Chapter 3.

Parameter	
R	The set of cabin crew classes, indexed by r
G^r	The duty-node based network for Class *r* of cabin crews
N_r	The set of nodes in the network for Class *r* of cabin crews, $n_r \in N_r$, $N_r = D_r \cup \{s, m\}$
A_r	The set of arcs in the network for Class *r* of cabin crews, $arc_{(n_r,n_r')} \in A_r$, $A_r = SA_r \cup EA_r \cup RA_r$
D_r	The set of duty nodes for Class *r* of cabin crews, indexed by d_k^r
$F_{d_k^r}$	The set of flights contained in duty node d_k^r
RA_r	The set of rest arcs, indexed by $arc_{(d_{k_1}^r,d_{k_2}^r)}$, linking duty nodes $d_{k_1}^r$ and $d_{k_2}^r$
SA_r	The set of starting arcs, indexed by $arc_{(s,d_k^r)}$, linking the source node to duty node d_k^r
EA_r	The set of ending arcs, indexed by $arc_{(d_k^r,m)}$, linking the duty node d_k^r to the sink node
s	The source node (home base)
m	The sink node (home base)
Θ	The set of resources that restrict the feasibility of individual pairings, indexed by τ
J_r	The set of individual pairings of Class *r* available cabin crews, indexed by j_r
J_r^e	The set of individual pairings of Class r extra cabin crew, indexed by j_r^e
J_t	The set of cabin crew team pairings, indexed by j_t;
b_i^r	The number of class r cabin crew required on flight i
q_i^r	The number of class r cabin crew assigned to flight i
c_{fa}	The fixed payment for an available cabin crew
c_{fe}	The fixed payment for an extra cabin crew
c_{j_r}	The cost of individual pairing j_r
$c_{j_r^e}$	The cost of individual pairing j_r^e
c_{j_t}	The cost of team pairing j_t;
a_{ij_r}	The binary flight coverage coefficient for individual pairing j_r of class r available cabin crew; a_{ij_r}=1 if individual pairing j_r covers flight i, otherwise 0
$a_{ij_r^e}$	The binary flight coverage coefficient for individual pairing j_r^e of class r extra cabin crew; $a_{ij_r^e}$=1 if individual pairing j_r^e covers flight i, otherwise 0
a_{ij_t}	The binary flight coverage coefficient for cabin crew team pairing j_t; a_{ij_t}=1 if team pairing j_t covers flight i, otherwise 0.
μ	The substitution penalty cost (also known as flight fluctuation coefficient)
M	The big penalty cost induced by the generation of an extra cabin crew individual pairing

d_r	The number of class r available cabin crews
MS	The minimum total manpower demand with CCS
MC_r	The minimum manpower demand for Class r without CCS
MM_r	The minimum manpower demand to satisfy the minimum satisfaction constraints for Class r
NA_r	The minimum-cost manpower demand for Class r
TA	The number of available cabin crews of all classes
ξ_x	The column associated with each decision variable in the models, $x = x_{j_r}$ or $x_{j_r^e}$
Q	The set of legal individual pairings identified in DPIA
U	The set of unprocessed partial paths in DPIA
O	The set of covered flights in DPIA
L	The last element in U
H	Each newly generated (partial) path by extending L
z	The flight in H that is not contained in O
RC_x	The reduced cost of decision variable x, $x = x_{j_r}$ or $x_{j_r^e}$
π_i	The dual price associated with the i_{th} row of Eqs. (3-7)
λ_i^r	The dual price associated with the i_{th} row of the r_{th} set of Eqs. (3-8)
θ_i^r	The dual price associated with the i_{th} row of the r_{th} set of Eqs. (3-9)
φ_r	The dual price associated with the r_{th} row of Eqs. (3-10)
$ac_{arc_{(n_r,n_r')}}$	The arc cost of $arc_{(n_r,n_r')}$ in PP, $n_r \in N_r$
nc_{n_r}	The duty node cost of node n_r in PP, $n_r \in N_r$
tac_{j_r}	The total arc node cost of path (pairing) j_r
tnc_{j_r}	The total node cost of path (pairing) j_r
tc_{j_r}	The total cost of path (pairing) j_r
Variable	
x_{j_t}	The binary decision variable for team pairing j_t; x_{j_t}=1 if team pairing j_t is selected, otherwise 0;
x_{j_r}	The nonnegative integer decision variable for individual pairing j_r of class r available cabin crew (the value taken represents the number of times the corresponding individual pairing is selected)
$x_{j_r^e}$	The nonnegative integer decision variable for individual pairing j_r of class r extra cabin crew (the value taken represents the number of times the corresponding individual pairing is selected)
s_i^r	The substitution recording variable of class r cabin crew on flight i (the value taken equals to the times of this class substituted by other classes on flight i)
Abbreviation	
CPP	Crew pairing problem
CAP	Crew assignment problem
CCS	Controlled crew substitution
MICCPP-ACCS	Multi-class cabin crew pairing problem with availability and controlled crew substitution
MICCPP-A	Multi-class cabin crew pairing problem with availability
TCCPP	Traditional cabin CPP problem
RMP	The restricted master problem in column generation
PP	The sub-problem in column generation
DPIA	Dynamic programming based initialization algorithm
FNDPC	Flight negative dual price cost
RCSPP	Resource constrained shortest path problem

Appendix B. Input Data and Operational Parameters for Chapter 3

Table B-1 summarizes the number of seats, doors and sections of each aircraft type and layout. Note that the number in brackets represents the number of sections in the corresponding cabin class. Let's take Type 5 as an example. Type 5 has two different cabin layouts (Type 5-1 and Type 5-2) with 340 and 275 seats in total, respectively. Type 5-1 has three cabin classes of a Business Class (40 seats), a Premium Economy Class (32 seats), and an Economy Class (268 seats). The Business Class has two sections, while the Premium Economy Class has only one section, and the Economy Class is divided into three sections. Therefore, Type 5-1 aircraft totally has six cabin sections with 10 doors.

Table B-1. Layout of the aircrafts involved in the selected flight schedules.

Aircraft type and layout	Number of seats					Number of	
	First Class	Business Class	Premium Economy Class	Economy Class	Total	Doors	Cabin sections
Type 1-1	0	24 (1)	0	293 (3)	317	8	4
Type 1-2	0	39 (2)	0	223 (2)	262	8	4
Type 1-3	0	39 (2)	21 (1)	191 (2)	251	8	5
Type 2	0	38 (2)	28 (1)	214 (2)	280	8	5
Type 3	0	42 (1)	0	293 (2)	335	8	3
Type 4	0	42 (1)	0	356 (3)	398	10	4
Type 5-1	0	40 (2)	32 (1)	268 (3)	340	10	6
Type 5-2	6 (1)	53 (2)	34 (1)	182 (2)	275	10	6

Apart from the minimum requirements imposed by aviation authorities (e.g., at least one cabin crew for each pair of airplane doors, for each separate cabin section, and for every 50 passengers), The Airways establishes a higher service level by assigning more cabin crews to the flights. In this study, the following standards are utilized: Every 4 passengers in the First Class, every 10 passengers in the Business Class, every 20 passengers in the Premium Economy Class, and every 40 passengers in the Economy Class are equipped with one cabin crew. Besides, classes 1 and 2 cabin crews are usually assigned with jobs in the First Class cabin and the Business Class cabin, while classes 3 and 4 cabin crews are generally allocated with those in the Premium Economy Class cabin and the Economy Class cabin. Accordingly, the number of cabin crews of each class required for each aircraft type and layout is obtained, as summarized in **Table B-2**.

Table B-2. Cabin crew requirements for the aircraft types and layouts.

Aircraft type and layout	Number of cabin crews required				
	Class 1	Class 2	Class 3	Class 4	Total
Type 1-1	1	2	4	4	11
Type 1-2	2	2	3	3	10
Type 1-3	2	2	3	4	11
Type 2	2	2	4	4	12
Type 3	2	3	4	4	13
Type 4	2	3	4	5	14
Type 5-1	2	2	4	5	13
Type 5-2	3	5	3	4	15

Appendix C. Computational Experiments Materials for Chapter 3

Table C-1. Number of constraints and size of the initial pool of the three models.

Instance	MICCPP-ACCS			MICCPP-A		TCCPP									
						Type 1		Type 2		Type 3		Type 4		Type 5	
	Constraints	Initial pool	s_i^r	Constraints	Initial pool	Constraints	Initial pool	Constraints	Initial pool	Constraints	Initial pool	Constraints	Initial pool	Constraints	Initial pool
I1	760	256	336	85	64	4	2	27	24	0	0	21	14	32	29
I2	769	264	340	86	66	5	3	29	25	0	0	23	15	28	24
I3	697	256	308	78	64	0	0	29	25	2	1	26	19	20	14
I4	769	264	340	86	66	18	14	25	19	0	0	28	20	14	9
I5	733	268	324	82	67	7	5	33	31	6	3	24	16	11	7
I6	697	244	308	78	61	14	9	33	29	2	1	14	9	14	9
I7	832	296	368	93	74	27	22	34	30	5	3	2	1	24	19
I8	751	276	332	84	69	21	17	37	32	2	1	10	7	13	8
Average	751	265.5	332	84.00	66.38	12	9	30.88	26.88	2.13	1.13	18.5	12.63	19.5	14.88

Table C-1 illustrates the number of constraints and size of the initial pool for the three models in the computational experiments, showing the higher problem complexity of the proposed MICCPP-ACCS. Note that MICCPP-ACCS has a special variable (substitution recording variable (s_i^r)) which does not exist in MICCPP-A and TCCPP. Therefore, the number of substitution recording variable (s_i^r) for MICCPP-ACCS in each instance is shown in the fourth column of the table. It is seen that the size of constraints for MICCPP-ACCS is much higher than that for MICCPP-A (8.94 times averagely). When comparing with TCCPP, it is observed that there are averagely 751 constraints in MICCPP-ACCS, while only 12 in type 1 TCCPP, 30.88 in type 2 TCCPP, 2.13 in type 3 TCCPP, 18.5 in type 4 TCCPP, and 19.5 in type 5 TCCPP. Regarding the initial pool, MICCPP-ACCS has the largest size which is four times the size of MICCPP-A. This is because that there are four classes of cabin crew variables in MICCPP-ACCS, while only one class in MICCPP-A. Besides, in TCCPP, the entire flight network is separated into smaller networks for each type of aircraft. Therefore, the size of the initial pool for each type of TCCPP is greatly reduced. On average, there are 265.5 initial cabin crew variables in MICCPP-ACCS, while only 9 in Type 1 TCCPP, 26.88 in Type 2 TCCPP, 1.13 in Type 3 TCCPP, 12.63 in Type 4 TCCPP, and 14.88 in Type 5 TCCPP.

Table C-2 depicts the details of scenarios when the derived cabin crew availability levels (Level 1, Level 2, and Level 3) are applied in each MICCPP-ACCS instance.

Table C-2. Details of the scenarios corresponding to the tested instances.

Availability level	Instance	Scenario	Manpower shortage	CCS	Extra manpower	Total extra crew demand
Level 1	I1-M	8				0
	I2-M	8				0
	I3-M	8				0
	I4-M	8				0
	I5-M	8				0
	I6-M	8				0
	I7-M	8				0
	I8-M	8				0
Level 2	I1-M	4	√	√	√	3
	I2-M	5	√	√		0
	I3-M	3	√		√	15
	I4-M	4	√	√	√	7
	I5-M	4	√	√	√	36
	I6-M	4	√	√	√	13
	I7-M	3	√		√	46
	I8-M	3	√		√	37
Level 3	I1-M	5	√	√		0
	I2-M	5	√	√		0
	I3-M	7	√	√	√	1
	I4-M	5	√	√		0
	I5-M	2	√	√	√	19
	I6-M	7	√	√	√	2
	I7-M	2	√	√	√	29
	I8-M	2	√	√	√	20

Table C-3 summarizes the solution details of the sum of all five aircraft types TCCPPs. In particular, the team pairings obtained in the solution are for cabin crew teams, rather than individuals. As a result, it is necessary to calculate the real manpower demand based on the obtained team pairings. Specifically, the real number of Class r cabin crews required for a team pairing equals the maximum demand for this class among all flights covered in the pairing. The second column in **Table C-3** represents the real total demand for cabin crews for each instance. Besides, the third and fourth columns show the real total TAFB cost and manpower utilization, respectively. The last three columns correspondingly represent the real average number of flights, average number of duties, and average length of pairings in the solution. When the cabin crew availability levels are considered, the corresponding extra manpower demand could be obtained by subtracting the availability quantity from the total real manpower demand, as shown in the 13th column in **Table C-4**. For example, the total real manpower demand for I1 in TCCPP is 668, while there are only 229 available cabin crews under Level 1. Accordingly, total 668-229=439 extra cabin crews are needed in this case. Therefore, based on the available manpower fixed cost (the 3rd column in **Table C-4**), the extra manpower fixed cost (the 14th column in **Table C-4**), and the TAFB cost (the 3rd column in **Table C-3**), the total cost for each instance of TCCPP under each availability level is obtained, as illustrated in the last column of **Table C-4**.

Table C-3. Solution details of TCCPP (all five aircraft types).

Instance	TCCPP solutions (all five aircraft types)					
	Total manpower used	TAFB cost	Utilization	Average number in a pairing		
				Flights	Duties	Elapsed time
I1 (T1-T5)	668	1084325	5.4%	2.00	1.90	1623.24
I2 (T1-T5)	664	1006420	5.5%	2.00	1.81	1515.69
I3 (T1-T5)	576	886865	5.8%	2.00	1.82	1539.70
I4 (T1-T5)	641	984960	5.5%	2.00	1.79	1536.60
I5 (T1-T5)	589	935330	5.8%	2.00	1.86	1588.00
I6 (T1-T5)	589	957935	5.3%	2.00	1.83	1626.38
I7 (T1-T5)	693	1237425	5.3%	2.00	1.89	1785.61
I8 (T1-T5)	630	1166215	5.3%	2.00	1.90	1851.13
Average	631.25	1032434	5.5%	2.00	1.85	1633.29

The 4th to 12th columns in **Table C-4** show the total manpower demand, total extra manpower demand, TAFB cost, extra manpower fixed cost, total cost, manpower utilization, average number of flights, average number of duties, and average length of pairings for each instance of MICCPP-ACCS when the three availability levels are applied.

Table C-4. Solution details of MICCPP-ACCS and TCCPP (all five aircraft types).

Availability level	Instance	Available manpower fixed cost	MICCPP-ACCS solutions									TCCPP (all five aircraft types)		
			Total manpower used	Extra manpower demand	TAFB cost	Extra manpower fixed cost	Total cost	Utilization	Average number in a pairing			Extra manpower demand	Extra manpower fixed cost	Total cost
									Flights	Duties	Elapsed time			
	I1	687000	229	0	899365	0	1586365	15.7%	4.99	3.40	3927.36	439	2634000	4405325
	I2	687000	229	0	932865	0	1619865	15.9%	5.07	3.55	4073.65	435	2610000	4303420
	I3	687000	229	0	888575	0	1575575	14.5%	4.60	3.38	3880.24	347	2082000	3655865
	I4	687000	229	0	917505	0	1604505	15.4%	4.96	3.52	4006.57	412	2472000	4143960
Level 1	I5	687000	229	0	946040	0	1633040	14.9%	4.82	3.53	4131.18	360	2160000	3782330
	I6	687000	229	0	931890	0	1618890	13.7%	4.68	3.47	4069.39	360	2160000	3804935
	I7	687000	229	0	1028915	0	1715915	16.1%	5.28	3.76	4493.08	464	2784000	4708425
	I8	687000	229	0	929095	0	1616095	14.5%	4.72	3.46	4057.18	401	2406000	4259215
	Average	687000	229	0	934281	0	1621281	15.1%	4.89	3.51	4079.83	402.25	2413500	4132934
	I1	543000	184	3	982655	18000	1543655	19.6%	6.24	4.22	5340.52	487	2922000	4549325
	I2	543000	181	0	1013765	0	1556765	20.1%	6.34	4.42	5600.91	483	2898000	4447420
	I3	543000	196	15	961525	90000	1594525	16.9%	5.52	4.02	4905.74	395	2370000	3799865
	I4	543000	188	7	1014955	42000	1599955	18.8%	6.04	4.24	5398.70	460	2760000	4287960
Level 2	I5	543000	217	36	972135	216000	1731135	15.8%	5.09	3.72	4479.88	408	2448000	3926330
	I6	543000	194	13	1028685	78000	1649685	16.2%	5.59	4.09	5302.50	408	2448000	3948935
	I7	543000	227	46	1040190	276000	1859190	16.2%	5.37	3.81	4582.33	512	3072000	4852425
	I8	543000	218	37	971340	222000	1736340	15.3%	5.00	3.67	4455.69	449	2694000	4403215
	Average	543000	200.63	19.63	998156	117750	1658906	17.4%	5.65	4.02	5008.28	450.25	2701500	4276934
	I1	594000	198	0	918535	0	1512535	18.2%	5.70	3.86	4639.07	470	2820000	4498325
	I2	594000	198	0	961090	0	1555090	18.4%	5.83	4.03	4853.99	466	2796000	4396420
	I3	594000	199	1	921600	6000	1521600	16.7%	5.28	3.87	4631.16	378	2268000	3748865
	I4	594000	198	0	972440	0	1566440	17.8%	5.69	4.01	4911.31	443	2658000	4236960
Level 3	I5	594000	217	19	1001545	114000	1709545	15.8%	5.12	3.77	4615.41	391	2346000	3875330
	I6	594000	200	2	1002075	12000	1608075	15.7%	5.39	3.93	5010.38	391	2346000	3897935
	I7	594000	227	29	1044290	174000	1812290	16.2%	5.39	3.82	4600.40	495	2970000	4801425
	I8	594000	218	20	957370	120000	1671370	15.3%	4.95	3.63	4391.61	432	2592000	4352215
	Average	594000	206.88	8.88	972368	53250	1619618	16.8%	5.42	3.87	4706.66	433.25	2599500	4225934
Overage average		608000	212.17	9.50	968269	57000	1633269	16.4%	5.31958	3.7994	4598.26	428.58	2571500	4211934

Table C-5 represents the relative performance of MICCPP-ACCS over TCCPP. Specifically, the third to fifth columns show the reduction percentage in total manpower used, extra manpower demand, and cost achieved by MICCPP-ACCS over TCCPP, while the sixth to ninth columns conclude the growth percentage in manpower utilization, and the average number of flights, average number of duties, and average length of elapsed time in the pairings generated.

Table C-5. Relative performance of MICCPP-ACCS over TCCPP.

Availability level	Instance	Relative performance of MICCPP-ACCS over TCCPP						
		Reduction			Increase (in a pairing)			
		Total manpower used	Extra manpower demand	Cost	Utilization	Average no. of flights	Average no. of duties	Average length of elapsed time
Level 1	I1	65.7%	100.0%	64.0%	191.7%	149.3%	79.1%	142.0%
	I2	65.5%	100.0%	62.4%	190.0%	153.3%	96.6%	168.8%
	I3	60.2%	100.0%	56.9%	151.5%	130.1%	85.0%	152.0%
	I4	64.3%	100.0%	61.3%	179.9%	148.0%	96.9%	160.7%
	I5	61.1%	100.0%	56.8%	157.2%	141.1%	90.0%	160.2%
	I6	61.1%	100.0%	57.5%	157.2%	134.1%	89.4%	150.2%
	I7	67.0%	100.0%	63.6%	202.6%	164.2%	99.6%	151.6%
	I8	63.7%	100.0%	62.1%	175.1%	136.2%	82.4%	119.2%
	Average	63.6%	100.0%	60.6%	175.7%	144.5%	89.9%	150.6%
Level 2	I1	72.5%	99.4%	66.1%	263.0%	212.0%	122.6%	229.0%
	I2	72.7%	100.0%	65.0%	**266.9%**	217.1%	144.9%	269.5%
	I3	66.0%	96.2%	58.0%	193.9%	176.0%	120.3%	218.6%
	I4	70.7%	98.5%	62.7%	241.0%	202.1%	137.2%	251.3%
	I5	63.2%	91.2%	55.9%	171.4%	154.4%	100.2%	182.1%
	I6	67.1%	96.8%	58.2%	203.6%	179.4%	122.9%	226.0%
	I7	67.2%	91.0%	61.7%	205.3%	168.7%	102.0%	156.6%
	I8	65.4%	91.8%	60.6%	189.0%	150.0%	93.6%	140.7%
	Average	68.1%	95.6%	61.0%	216.8%	182.5%	118.0%	209.2%
Level 3	I1	70.4%	100.0%	**66.4%**	237.4%	184.9%	103.4%	185.8%
	I2	70.2%	100.0%	64.6%	235.4%	191.4%	122.9%	220.3%
	I3	65.5%	99.7%	59.4%	189.5%	163.8%	112.1%	200.8%
	I4	69.1%	100.0%	63.0%	223.7%	184.3%	124.1%	219.6%
	I5	63.2%	95.1%	55.9%	171.4%	156.2%	103.0%	190.6%
	I6	66.0%	99.5%	58.8%	194.5%	169.5%	114.6%	208.1%
	I7	67.2%	94.1%	62.3%	205.3%	169.6%	102.8%	157.6%
	I8	65.4%	95.4%	61.6%	189.0%	147.7%	91.5%	137.2%
	Average	67.1%	98.0%	61.5%	205.8%	170.9%	109.3%	190.0%
Overall average		66.3%	97.9%	**61.0%**	**199.4%**	166.0%	105.7%	183.3%

Table C-6 summarizes the computation time of MICCPP-ACCS under each availability level. The overall average computation time for the three availability levels is 24.193s. **Table C-7** gives the computation time of TCCPP. As TCCPP ignores the manpower availability limitation, the solution process under all the three availability levels are the same for each instance. Besides, as discussed, TCCPP is solved within each separate aircraft type. Therefore, **Table C-7** shows that (i) the average computation time across all five aircraft types of each instance, and (ii) the total computation time for all five aircraft types of each instance. To be specific, for TCCPP, the average total computation time is 0.333s. In the numerical instances, optimal solutions could be identified within reasonable computation times using the proposed MICCPP-ACCS.

Table C-6. Computation time of MICCPP-ACCS.

Instance	Level 1 - Computation time (s)				Level 2 - Computation time (s)				Level 3 -Computation time (s)			
	Column generation	Pricing problem	Branch-and-Bound	Total	Column generation	Pricing problem	Branch-and-Bound	Total	Column generation	Pricing problem	Branch-and-Bound	Total
I1-M	20.779	19.444	0.342	21.121	37.666	35.391	0.527	38.193	19.796	18.395	0.651	20.447
I2-M	19.321	17.885	0.632	19.953	32.749	31.010	10.019	42.768	18.182	16.690	0.894	19.076
I3-M	12.409	11.293	0.147	12.556	14.782	13.687	0.210	14.992	11.722	10.662	0.760	12.482
I4-M	23.296	21.587	0.368	23.664	42.613	40.475	0.990	43.603	23.485	21.854	1.776	25.261
I5-M	19.638	17.980	0.163	19.801	25.105	23.235	0.494	25.599	23.806	22.150	0.748	24.554
I6-M	12.747	11.621	0.050	12.797	13.637	12.493	0.868	14.505	8.155	7.212	0.616	8.771
I7-M	33.996	32.301	6.008	40.004	34.040	32.041	0.873	34.913	37.435	35.140	0.444	37.879
I8-M	19.723	17.817	3.164	22.887	20.047	18.145	0.328	20.375	24.131	21.604	0.296	24.427
Average	20.239	18.741	1.359	**21.598**	27.580	25.810	1.789	**29.369**	20.839	19.213	0.773	**21.612**

Table C-7. Computation time of TCCPP (five networks).

Instance	Average computation time (s)				Total computation time (s)			
	Column generation	Pricing problem	Branch-and-Bound	Total	Column generation	Pricing problem	Branch-and-Bound	Total
I1-(T1-T5)	0.059	0.005	0.007	0.066	0.296	0.027	0.036	0.332
I2-(T1-T5)	0.058	0.003	0.003	0.060	0.288	0.015	0.013	0.301
I3-(T1-T5)	0.052	0.002	0.005	0.057	0.259	0.011	0.024	0.283
I4-(T1-T5)	0.053	0.002	0.002	0.055	0.265	0.012	0.010	0.275
I5-(T1-T5)	0.074	0.003	0.003	0.077	0.370	0.013	0.016	0.386
I6-(T1-T5)	0.068	0.002	0.003	0.072	0.341	0.009	0.017	0.358
I7-(T1-T5)	0.071	0.004	0.003	0.075	0.356	0.020	0.017	0.373
I8-(T1-T5)	0.068	0.005	0.003	0.072	0.342	0.024	0.017	0.359
Average	0.063	0.003	0.004	**0.067**	0.315	0.016	0.019	**0.333**

Appendix D. Notation and Thresholds for Chapter 4

Table D-1 summarizes the important notation used in the analyses (both in the main context and in the online mathematical proofs).

Table D-1. Important notation used in Chapter 4.

Notation	Remarks	Notation	Remarks
$S_1 = (1-\theta)^2\sigma^2$	$1 \ge S_1 \ge 0$	$T_3 = 1 + S_1k_1$	$2 \ge T_3 \ge 1$
$S_2 = \theta^2\sigma^2$	$1 \ge S_2 \ge 0$	$T_4 = 1 + S_2k_2$	$2 \ge T_4 \ge 1$
$A_1 = 2(1+S_1k_1)$	$4 \ge A_1 \ge 2$	$\eta_1 = 1 + 2k_1\delta^2$	$3 \ge \eta_1 \ge 1$
$A_2 = 2(1+S_2k_2)$	$4 \ge A_2 \ge 2$	$\eta_2 = 1 + 2k_2\delta^2$	$3 \ge \eta_2 \ge 1$
$A_3 = (1-\theta)a_0 + c_1(1+2S_1k_1)$	$4 \ge A_3 \ge 0$	$B_1 = 2(1+S_1k_1+k_1\delta^2)$	$6 \ge B_1 \ge 2$
$A_4 = \theta a_0 + c_2(1+2S_2k_2)$	$4 \ge A_4 \ge 0$	$B_2 = 2(1+S_2k_2+k_2\delta^2)$	$6 \ge B_2 \ge 2$
$T_1 = 1+2S_1k_1$	$3 \ge T_1 \ge 1$	$B_3 = (1-\theta)a_0(1+2k_1\delta^2) + c_{10}(1+2S_1k_1)$	$6 \ge B_3 \ge 0$
$T_2 = 1+2S_2k_2$	$3 \ge T_2 \ge 1$	$B_4 = \theta a_0(1+2k_2\delta^2) + c_{20}(1+2S_2k_2)$	$6 \ge B_4 \ge 0$

The crucial relative risk-averse attitude thresholds identified in the analyses are listed in **Table D-2**. It could be seen that each pair of relative risk-averse attitude thresholds for the two carriers are perfectly symmetric (e.g., Λ_1 and Λ_2).

Table D-2. Crucial relative risk-averse attitude thresholds identified in the analyses.

Λ_1	$\dfrac{\lambda^2\theta^2T_1}{(1-\theta)^2A_2\left(A_2-\lambda^2\right)}$	ϑ_1	$\dfrac{\lambda^2\eta_1(B_2-\eta_2)}{B_2(B_2-\lambda^2\eta_2)}$
Λ_2	$\dfrac{\lambda^2(1-\theta)^2T_2}{\theta^2A_1\left(A_1-\lambda^2\right)}$	ϑ_2	$\dfrac{\lambda^2\eta_2(B_1-\eta_1)}{B_1(B_1-\lambda^2\eta_1)}$
Ω_2	$\dfrac{(1-\theta)^2A_2T_2}{\theta^2\left(A_1-\lambda^2\right)}$	ς_1	$\dfrac{B_1(B_2-\eta_2)}{\eta_2(B_2-\lambda^2\eta_2)}$
Ω_1	$\dfrac{\theta^2A_1T_1}{(1-\theta)^2\left(A_2-\lambda^2\right)}$	ς_2	$\dfrac{B_2(B_1-\eta_1)}{\eta_1(B_1-\lambda^2\eta_1)}$

Besides, **Table D-3** concludes the important cost thresholds for the two carriers in determining the impacts of diverse parameters on the optimal prices. It is seen that all pairs of cost thresholds are perfectly symmetric (e.g., CT_1 and CT_2).

Table D-3. Crucial cost thresholds identified in the analyses.

CT_1	$\dfrac{2(1+S_2k_2)(1-\theta)a_0+\lambda\left[\theta a_0+c_2(1+2S_2k_2)\right]}{2(1+S_2k_2)-\lambda^2}$
CT_2	$\dfrac{2(1+S_1k_1)\theta a_0+\lambda\left[(1-\theta)a_0+c_1(1+2S_1k_1)\right]}{2(1+S_1k_1)-\lambda^2}$
DT_1	$\dfrac{a_0\left(\lambda-A_2\right)\left(A_1A_2-\lambda^2\right)+4\sigma^2\left\{\begin{matrix}k_1\left(1-\theta\right)A_2a_0\left[A_2\left(1-\theta\right)+\lambda\theta\right]\text{-}\lambda k_2\theta a_0\left[\theta A_1+\lambda(1-\theta)\right]\\+[k_1\left(1-\theta\right)A_2(1+2S_2k_2)+k_2\theta\left(A_1-\lambda^2\right)]\lambda c_2\end{matrix}\right\}}{4\sigma^2\left[k_1\left(1-\theta\right)A_2\left(A_2-\lambda^2\right)+\lambda^2k_2\theta T_1\right]}$
DT_2	$\dfrac{a_0\left(\lambda-A_1\right)\left(A_1A_2-\lambda^2\right)+4\sigma^2\left\{\begin{matrix}k_2\theta A_1a_0[A_1\theta+\lambda(1-\theta)]-\lambda k_1\left(1-\theta\right)a_0\left[\left(1-\theta\right)A_2+\lambda\theta\right]\\+[k_2\theta A_1(1+2S_1k_1)+k_1\left(1-\theta\right)\left(A_2-\lambda^2\right)]\lambda c_1\end{matrix}\right\}}{4\sigma^2\left[k_2\theta A_1\left(A_1-\lambda^2\right)+\lambda^2k_1\left(1-\theta\right)T_2\right]}$
ET_1	$\dfrac{a_0\left(A_1-\lambda\right)\left(A_1A_2-\lambda^2\right)+4\sigma^2\left\{\begin{matrix}-k_2\theta A_1a_0\left[A_1\theta+(1-\theta)\lambda\right]+\lambda k_1\left(1-\theta\right)a_0\left[\left(1-\theta\right)A_2+\lambda\theta\right]\\+[k_2\theta A_1\left(A_1-\lambda^2\right)+\lambda^2k_1\left(1-\theta\right)(1+2S_2k_2)]c_2\end{matrix}\right\}}{4\sigma^2\left[k_2\theta A_1\lambda T_1+\lambda k_1\left(1-\theta\right)\left(A_2-\lambda^2\right)\right]}$
ET_2	$\dfrac{a_0\left(A_2-\lambda\right)\left(A_1A_2-\lambda^2\right)+4\sigma^2\left\{\begin{matrix}-k_1\left(1-\theta\right)A_2a_0\left[A_2\left(1-\theta\right)+\theta\lambda\right]+\lambda k_2\theta a_0[\theta A_1+\lambda(1-\theta)]\\+[k_1\left(1-\theta\right)A_2\left(A_2-\lambda^2\right)+\lambda^2k_2\theta(1+2S_1k_1)]c_1\end{matrix}\right\}}{4\sigma^2\left[k_1\left(1-\theta\right)A_2\lambda T_2+\lambda k_2\theta\left(A_1-\lambda^2\right)\right]}$
YT_1	$\dfrac{a_0\left[k_1\left(1-\theta\right)^2A_2\left[\left(1-\theta\right)A_2+\lambda\theta\right]+\lambda k_2\theta^2\left[\theta A_1+\lambda(1-\theta)\right]\right]-c_2\left[\lambda k_2\theta^2\left(A_1-\lambda^2\right)-k_1\left(1-\theta\right)^2A_2\lambda T_2\right]}{k_1\left(1-\theta\right)^2A_2\left(A_2-\lambda^2\right)-\lambda^2k_2\theta^2T_1}$
YT_2	$\dfrac{a_0\left[k_2\theta^2A_1\left[\theta A_1+\lambda(1-\theta)\right]+\lambda k_1\left(1-\theta\right)^2\left[\left(1-\theta\right)A_2+\lambda\theta\right]\right]-c_1\left[\lambda k_1\left(1-\theta\right)^2\left(A_2-\lambda^2\right)-k_2\theta^2A_1\lambda T_1\right]}{k_2\theta^2A_1\left(A_1-\lambda^2\right)-\lambda^2k_1\left(1-\theta\right)^2T_2}$
PT_1	$\dfrac{a_0\left[k_2\theta^2A_1\left[\theta A_1+\lambda(1-\theta)\right]+\lambda k_1\left(1-\theta\right)^2\left[\left(1-\theta\right)A_2+\lambda\theta\right]\right]-c_2\left[k_2\theta^2A_1\left(A_1-\lambda^2\right)-\lambda^2k_1\left(1-\theta\right)^2T_2\right]}{\lambda k_1\left(1-\theta\right)^2\left(A_2-\lambda^2\right)-k_2\theta^2A_1\lambda T_1}$
PT_2	$\dfrac{a_0\left[k_1\left(1-\theta\right)^2A_2\left[\left(1-\theta\right)A_2+\lambda\theta\right]+\lambda k_2\theta^2\left[\theta A_1+\lambda(1-\theta)\right]\right]-c_1\left[k_1\left(1-\theta\right)^2A_2\left(A_2-\lambda^2\right)-\lambda^2k_2\theta^2T_1\right]}{\lambda k_2\theta^2\left(A_1-\lambda^2\right)-k_1\left(1-\theta\right)^2A_2\lambda T_2}$
WT_1	$\dfrac{\begin{matrix}[k_2\lambda\eta_1(B_1-\lambda^2\eta_1)-k_1B_2\lambda(B_1-\eta_1)]B_4+[k_1B_2(B_2-\lambda^2\eta_2)-k_2\lambda^2\eta_1(B_2-\eta_2)](1-\theta)a_0\eta_1\\-[(1-\theta)a_0k_1B_2+\lambda k_2\eta_1\theta a_0](B_1B_2-\lambda^2\eta_1\eta_2)\end{matrix}}{[k_2\lambda^2\eta_1(B_2-\eta_2)+k_1B_2(\lambda^2\eta_2-B_2)](1+2S_1k_1)}$
WT_2	$\dfrac{\begin{matrix}[k_1\lambda\eta_2(B_2-\lambda^2\eta_2)-k_2B_1\lambda(B_2-\eta_2)]B_3+[k_2B_1(B_1-\lambda^2\eta_1)-k_1\lambda^2\eta_2(B_1-\eta_1)]\theta a_0\eta_2\\-[\theta a_0k_2B_1+\lambda k_1\eta_2(1-\theta)a_0](B_1B_2-\lambda^2\eta_1\eta_2)\end{matrix}}{[k_1\lambda^2\eta_2(B_1-\eta_1)+k_2B_1(\lambda^2\eta_1-B_1)](1+2S_2k_2)}$
UT_1	$\dfrac{\begin{matrix}[k_2B_1(B_1-\lambda^2\eta_1)-k_1\lambda^2\eta_2(B_1-\eta_1)]B_4+[k_1\lambda\eta_2(B_2-\lambda^2\eta_2)-k_2B_1\lambda(B_2-\eta_2)](1-\theta)a_0\eta_1\\-[\theta a_0k_2B_1+\lambda k_1\eta_2(1-\theta)a_0](B_1B_2-\lambda^2\eta_1\eta_2)\end{matrix}}{[k_2B_1\lambda(B_2-\eta_2)+k_1\lambda\eta_2(\lambda^2\eta_2-B_2)](1+2S_1k_1)}$
UT_2	$\dfrac{\begin{matrix}[k_1B_2(B_2-\lambda^2\eta_2)-k_2\lambda^2\eta_1(B_2-\eta_2)]B_3+[k_2\lambda\eta_1(B_1-\lambda^2\eta_1)-k_1B_2\lambda(B_1-\eta_1)]\theta a_0\eta_2\\-[(1-\theta)a_0k_1B_2+\lambda k_2\eta_1\theta a_0](B_1B_2-\lambda^2\eta_1\eta_2)\end{matrix}}{[k_1B_2\lambda(B_1-\eta_1)+k_2\lambda\eta_1(\lambda^2\eta_1-B_1)](1+2S_2k_2)}$

Appendix E. All Proofs for Chapter 4

Basic model

Proof of Lemma 1. Checking the second-order derivatives of Eq. (4-8) and Eq. (4-9), it is found that $\frac{\partial^2 O_1}{\partial (P_1)^2} = -2 - 2S_1k_1 < 0$ and $\frac{\partial^2 O_2}{\partial (P_2)^2} = -2 - 2S_2k_2 < 0$, which shows that both objective functions are concave in the respective unit price. Consequently, the reactive functions for the two players could be obtained through solving the first-order conditions as follows:

$$P_1 = \arg_{P_1}\left\{\frac{\partial O_1}{\partial P_1} = 0\right\} \rightarrow P_1 / P_2 = \frac{(1-\theta)a_0 + \lambda P_2 + c_1(1+2S_1k_1)}{2(1+S_1k_1)}$$

$$P_2 = \arg_{P_2}\left\{\frac{\partial O_2}{\partial P_2} = 0\right\} \rightarrow P_2 / P_1 = \frac{\theta a_0 + \lambda P_1 + c_2(1+2S_2k_2)}{2(1+S_2k_2)}$$

Solving the reactive functions, the optimal prices (P_1^* and P_2^*) for the two carriers could be identified. Besides, $A_1A_2 > \lambda^2$ always holds. (Q.E.D.)

Proposition 1

(i) Checking the first-order derivatives of P_1^* and P_2^* with respect to λ, it is found that $\frac{\partial P_1^*}{\partial \lambda} = \frac{1}{\left[A_1A_2 - \lambda^2\right]^2}\left\{A_4\left(A_1A_2 - \lambda^2\right) + \left(A_2A_3 + \lambda A_4\right)2\lambda\right\}$ and

$$\frac{\partial P_2^*}{\partial \lambda} = \frac{1}{\left[A_1A_2 - \lambda^2\right]^2}\left\{A_3\left(A_1A_2 - \lambda^2\right) + \left(A_1A_4 + \lambda A_3\right)2\lambda\right\}.$$

It is easily seen that $\frac{\partial P_1^*}{\partial \lambda} \geq 0, \frac{\partial P_2^*}{\partial \lambda} \geq 0$. (Q.E.D.)

(ii) When $\lambda > 0$, checking the first-order derivatives of P_1^* and P_2^* with respect to c_1 and c_2, it is obtained that $\frac{\partial P_1^*}{\partial c_1} = \frac{2(1+S_2k_2)(1+2S_1k_1)}{4(1+S_1k_1)(1+S_2k_2) - \lambda^2} > 0$,

$$\frac{\partial P_2^*}{\partial c_2}=\frac{2(1+S_1k_1)(1+2S_2k_2)}{4(1+S_1k_1)(1+S_2k_2)-\lambda^2}>0,\ \frac{\partial P_1^*}{\partial c_2}=\frac{\lambda(1+2S_2k_2)}{4(1+S_1k_1)(1+S_2k_2)-\lambda^2}>0, \text{ and}$$

$$\frac{\partial P_2^*}{\partial c_1}=\frac{\lambda(1+2S_1k_1)}{4(1+S_1k_1)(1+S_2k_2)-\lambda^2}>0.$$

Besides, it is found that $\frac{\partial P_1^*}{\partial c_1}>\frac{\partial P_1^*}{\partial c_2}$ and $\frac{\partial P_2^*}{\partial c_2}>\frac{\partial P_2^*}{\partial c_1}$. (Q.E.D.)

(iii) When $\lambda=0$, checking the first-order derivatives of P_1^* and P_2^* with respect to c_1 and c_2, it is identified that $\frac{\partial P_1^*}{\partial c_2}=0$, $\frac{\partial P_2^*}{\partial c_1}=0$,

$$\frac{\partial P_1^*}{\partial c_1}=\frac{2(1+S_2k_2)(1+2S_1k_1)}{4(1+S_1k_1)(1+S_2k_2)-\lambda^2}>0 \text{ and } \frac{\partial P_2^*}{\partial c_2}=\frac{2(1+S_1k_1)(1+2S_2k_2)}{4(1+S_1k_1)(1+S_2k_2)-\lambda^2}>0.$$

(Q.E.D.)

Proof of Proposition 2

Regarding k_1, the first-order derivatives of P_1^* and P_2^* are as follows:

$$\frac{\partial P_1^*}{\partial k_1}=\frac{2A_2(1-\theta)^2\sigma^2}{\left[A_1A_2-\lambda^2\right]^2}\left[-A_2(1-\theta)a_0-\lambda A_4+c_1(A_2-\lambda^2)\right], \text{ and}$$

$$\frac{\partial P_2^*}{\partial k_1}=\frac{2\lambda(1-\theta)^2\sigma^2}{\left[A_1A_2-\lambda^2\right]^2}\left[-A_2(1-\theta)a_0-\lambda A_4+c_1(A_2-\lambda^2)\right].$$ For k_2, it is obtained that

$$\frac{\partial P_1^*}{\partial k_2}=\frac{2\lambda\theta^2\sigma^2}{\left[A_1A_2-\lambda^2\right]^2}\left[-A_1\theta a_0-\lambda A_3+c_2\left(A_1-\lambda^2\right)\right], \text{ and}$$

$$\frac{\partial P_2^*}{\partial k_2}=\frac{2A_1\theta^2\sigma^2}{\left[A_1A_2-\lambda^2\right]^2}\left[-A_1\theta a_0-\lambda A_3+c_2\left(A_1-\lambda^2\right)\right].$$

(i) When $\sigma=0$, it is found that $\frac{\partial P_1^*}{\partial k_1}=\frac{\partial P_2^*}{\partial k_1}=\frac{\partial P_1^*}{\partial k_2}=\frac{\partial P_2^*}{\partial k_2}=0$. (Q.E.D.)

(ii) When $\sigma\neq 0$,

a) When $0<\theta<1$ and $\lambda>0$, if

$$c_1>(<)\frac{2(1+S_2k_2)(1-\theta)a_0+\lambda\left[\theta a_0+c_2(1+2S_2k_2)\right]}{2(1+S_2k_2)-\lambda^2}=CT_1,$$ then, it is obtained that

$\frac{\partial P_1^*}{\partial k_1}, \frac{\partial P_2^*}{\partial k_1} > (<) 0$. Besides, if

$c_2 > (<) \frac{2(1+S_1k_1)\theta a_0 + \lambda\left[(1-\theta)a_0 + c_1(1+2S_1k_1)\right]}{2(1+S_1k_1)-\lambda^2} = CT_2$, then, it is identified that

$\frac{\partial P_1^*}{\partial k_2}, \frac{\partial P_2^*}{\partial k_2} > (<) 0$. Besides, it could be identified that $\frac{\partial CT_r}{\partial c_{3-r}} > 0$. (Q.E.D.)

b) When $\lambda = 0$, it is obtained that $\frac{\partial CT_r}{\partial c_{3-r}} = 0$, and $\frac{\partial P_2^*}{\partial k_1} = \frac{\partial P_1^*}{\partial k_2} = 0$. (Q.E.D.)

c) When $\theta = 0$, it is found that $\frac{\partial P_1^*}{\partial k_2} = \frac{\partial P_2^*}{\partial k_2} = 0$; When $\theta = 1$, it is obtained that

$\frac{\partial P_1^*}{\partial k_1} = \frac{\partial P_2^*}{\partial k_1} = 0$. (Q.E.D.)

Proof of Proposition 3

Checking the first order derivatives of P_1^* and P_2^* with respect to θ, it is found that:

$$\frac{\partial P_1^*}{\partial \theta} = \frac{1}{\left[A_1A_2-\lambda^2\right]^2}\left\langle \begin{array}{l} a_0(\lambda - A_2)\left(A_1A_2-\lambda^2\right)+ \\ 4\sigma^2\left\{k_1(1-\theta)A_2\left[A_2(1-\theta)a_0+\lambda A_4+c_1\left(\lambda^2-A_2\right)\right]+\lambda k_2\theta\left[c_2\left(A_1-\lambda^2\right)-\theta a_0A_1-\lambda A_3\right]\right\}\end{array}\right\rangle$$

and

$$\frac{\partial P_2^*}{\partial \theta} = \frac{1}{\left[A_1A_2-\lambda^2\right]^2}\left\langle \begin{array}{l} a_0(A_1-\lambda)\left(A_1A_2-\lambda^2\right)+ \\ 4\sigma^2\left\{k_2\theta A_1\left[-A_1\theta a_0-\lambda A_3+c_2\left(A_1-\lambda^2\right)\right]+\lambda k_1(1-\theta)\left[c_1\left(\lambda^2-A_2\right)+(1-\theta)a_0A_2+\lambda A_4\right]\right\}\end{array}\right\rangle$$

.

(i) If $\sigma = 0$, it is identified that $\frac{\partial P_1^*}{\partial \theta} \le 0$ (which equals $\frac{\partial P_1^*}{\partial (1\text{-}\theta)} \ge 0$) and $\frac{\partial P_2^*}{\partial \theta} \ge 0$.

(Q.E.D.)

(ii) When $\sigma \ne 0$,

a) With competition ($\lambda > 0$), for carrier 1, it is obtained that $\frac{\partial P_1^{BD*}}{\partial \theta} < (>) 0$ (which

equals $\frac{\partial P_1^*}{\partial (1\text{-}\theta)} > (<) 0$) when

$$c_1 > (<) \frac{a_0(\lambda - A_2)(A_1A_2-\lambda^2)+4\sigma^2\left\{k_1(1-\theta)A_2a_0\left[A_2(1-\theta)+\lambda\theta\right]-\lambda k_2\theta a_0\left[\theta A_1+\lambda(1-\theta)\right]+[k_1(1-\theta)A_2(1+2S_2k_2)+k_2\theta(A_1-\lambda^2)]\lambda c_2\right\}}{4\sigma^2\left[k_1(1-\theta)A_2(A_2-\lambda^2)+\lambda^2k_2\theta T_1\right]} = DT_1$$

is satisfied. For carrier 2, it is found that $\frac{\partial P_2^{BD*}}{\partial\theta} > (<) 0$ when

$$c_2 > (<) \frac{a_0(\lambda - A_1)(A_1A_2-\lambda^2)+4\sigma^2\left\{k_2\theta A_1a_0[A_1\theta+\lambda(1-\theta)]-\lambda k_1(1-\theta)a_0\left[(1-\theta)A_2+\lambda\theta\right]+[k_2\theta A_1(1+2S_1k_1)+k_1(1-\theta)(A_2-\lambda^2)]\lambda c_1\right\}}{4\sigma^2\left[k_2\theta A_1(A_1-\lambda^2)+\lambda^2k_1(1-\theta)T_2\right]} = DT_2$$

is satisfied. Besides, it is obtained that $\frac{\partial DT_r}{\partial c_{3-r}} > 0$ (when $\lambda > 0$). (Q.E.D.)

b) With competition ($\lambda > 0$), for carrier 2, it is identified that $\frac{\partial P_2^{BD*}}{\partial\theta} < (>) 0$ (which equals $\frac{\partial P_1^*}{\partial\,(1\text{-}\theta)} > (<) 0$) when

$$c_1 > (<) \frac{a_0(A_1 - \lambda)(A_1A_2-\lambda^2)+4\sigma^2\left\{-k_2\theta A_1a_0\left[A_1\theta+(1-\theta)\lambda\right]+\lambda k_1(1-\theta)a_0\left[(1-\theta)A_2+\lambda\theta\right]+[k_2\theta A_1(A_1-\lambda^2)+\lambda^2k_1(1-\theta)(1+2S_2k_2)]c_2\right\}}{4\sigma^2\left[k_2\theta A_1\lambda T_1+\lambda k_1(1-\theta)(A_2-\lambda^2)\right]} = ET_1$$

is satisfied. For carrier 1, it is identified that $\frac{\partial P_1^{BD*}}{\partial\theta} > (<) 0$ when

$$c_2 > (<) \frac{a_0(A_2 - \lambda)(A_1A_2-\lambda^2)+4\sigma^2\left\{-k_1(1-\theta)A_2a_0\left[A_2(1-\theta)+\theta\lambda\right]+\lambda k_2\theta a_0[\theta A_1+\lambda(1-\theta)]+[k_1(1-\theta)A_2(A_2-\lambda^2)+\lambda^2k_2\theta(1+2S_1k_1)]c_1\right\}}{4\sigma^2\left[k_1(1-\theta)A_2\lambda T_2+\lambda k_2\theta(A_1-\lambda^2)\right]} = ET_2$$

is satisfied. Besides, $\frac{\partial ET_{3-r}}{\partial c_r} > 0$. (Q.E.D.)

c) Without competition ($\lambda = 0$), it is found that

$$\frac{\partial P_1^*}{\partial\theta} = \frac{1}{A_1^2}[2a_0(k_1S_1-1)-4\sigma^2k_1(1-\theta)c_1] < 0 \text{ and}$$

$$\frac{\partial P_2^*}{\partial\theta} = \frac{1}{A_2^2}[2a_0(1-k_2S_2)+4\sigma^2k_2\theta c_2] > 0. \quad \text{(Q.E.D.)}$$

Proof of Proposition 4

Checking the first order derivatives of P_1^* and P_2^* with respect to σ, it is found that

$$\frac{\partial P_1^*}{\partial\sigma} = \frac{4\sigma}{\left[A_1A_2-\lambda^2\right]^2}\left\{\begin{array}{l} c_1\left[k_1(1-\theta)^2A_2(A_2-\lambda^2)-\lambda^2k_2\theta^2T_1\right]+c_2\left[\lambda k_2\theta^2(A_1-\lambda^2)-k_1(1-\theta)^2A_2\lambda T_2\right] \\ -a_0\left[k_1(1-\theta)^2A_2\left[(1-\theta)A_2+\lambda\theta\right]+\lambda k_2\theta^2\left[\theta A_1+\lambda(1-\theta)\right]\right] \end{array}\right\}$$

and

$$\frac{\partial P_2^*}{\partial \sigma}=\frac{4\sigma}{\left[A_1A_2-\lambda^2\right]^2}\begin{Bmatrix} c_2\left[k_2\theta^2A_1\left(A_1-\lambda^2\right)-\lambda^2k_1\left(1-\theta\right)^2T_2\right]+c_1\left[\lambda k_1\left(1-\theta\right)^2\left(A_2-\lambda^2\right)-k_2\theta^2A_1\lambda T_1\right] \\ -a_0\left[k_2\theta^2A_1\left[\theta A_1+\lambda(1-\theta)\right]+\lambda k_1\left(1-\theta\right)^2\left[\left(1-\theta\right)A_2+\lambda\theta\right]\right] \end{Bmatrix}$$

.

(i) When $0<\theta<1$ and $\lambda>0$,

Let $\Lambda_1=\frac{\lambda^2\theta^2T_1}{\left(1-\theta\right)^2A_2\left(A_2-\lambda^2\right)}$, $\Omega_2=\frac{\left(1-\theta\right)^2A_2T_2}{\theta^2\left(A_1-\lambda^2\right)}$, and $\Lambda_2=\frac{\lambda^2\left(1-\theta\right)^2T_2}{\theta^2A_1\left(A_1-\lambda^2\right)}$, and

$\Omega_1=\frac{\theta^2A_1T_1}{\left(1-\theta\right)^2\left(A_2-\lambda^2\right)}$.

a) For carrier 1, when $\tau_1>\Lambda_1$, when c_1 is sufficiently large, that is,

$$c_1>\frac{a_0\left[k_1\left(1-\theta\right)^2A_2\left[\left(1-\theta\right)A_2+\lambda\theta\right]+\lambda k_2\theta^2\left[\theta A_1+\lambda(1-\theta)\right]\right]-c_2\left[\lambda k_2\theta^2\left(A_1-\lambda^2\right)-k_1\left(1-\theta\right)^2A_2\lambda T_2\right]}{k_1\left(1-\theta\right)^2A_2\left(A_2-\lambda^2\right)-\lambda^2k_2\theta^2T_1}=YT_1$$

, then it is identified that $\frac{\partial P_1^*}{\partial \sigma}>0$. For carrier 2, if $\tau_2>\Lambda_2$, if c_2 is sufficiently large, that is,

$$c_2>\frac{a_0\left[k_2\theta^2A_1\left[\theta A_1+\lambda(1-\theta)\right]+\lambda k_1\left(1-\theta\right)^2\left[\left(1-\theta\right)A_2+\lambda\theta\right]\right]-c_1\left[\lambda k_1\left(1-\theta\right)^2\left(A_2-\lambda^2\right)-k_2\theta^2A_1\lambda T_1\right]}{k_2\theta^2A_1\left(A_1-\lambda^2\right)-\lambda^2k_1\left(1-\theta\right)^2T_2}=YT_2$$

, then it is found that $\frac{\partial P_2^*}{\partial \sigma}>0$. (Q.E.D.)

b) For carrier 2, when $\tau_1>\Omega_1$, when c_1 is sufficiently large, that is,

$$c_1>\frac{a_0\left[k_2\theta^2A_1\left[\theta A_1+\lambda(1-\theta)\right]+\lambda k_1\left(1-\theta\right)^2\left[\left(1-\theta\right)A_2+\lambda\theta\right]\right]-c_2\left[k_2\theta^2A_1\left(A_1-\lambda^2\right)-\lambda^2k_1\left(1-\theta\right)^2T_2\right]}{\lambda k_1\left(1-\theta\right)^2\left(A_2-\lambda^2\right)-k_2\theta^2A_1\lambda T_1}=PT_1$$

, then it is identified that $\frac{\partial P_2^*}{\partial \sigma}>0$. For carrier 1, when $\tau_2>\Omega_2$, if c_2 is sufficiently large, that is,

$$c_2>\frac{a_0\left[k_1\left(1-\theta\right)^2A_2\left[\left(1-\theta\right)A_2+\lambda\theta\right]+\lambda k_2\theta^2\left[\theta A_1+\lambda(1-\theta)\right]\right]-c_1\left[k_1\left(1-\theta\right)^2A_2\left(A_2-\lambda^2\right)-\lambda^2k_2\theta^2T_1\right]}{\lambda k_2\theta^2\left(A_1-\lambda^2\right)-k_1\left(1-\theta\right)^2A_2\lambda T_2}=PT_2$$

, then $\frac{\partial P_1^*}{\partial \sigma}>0$. (Q.E.D.)

(ii) When $0 < \theta < 1$ and $\lambda = 0$, it is identified that

$\frac{\partial P_1^*}{\partial \sigma} = \frac{4\sigma k_1 (1-\theta)^2 A_2^2}{(A_1 A_2)^2}[c_1 - a_0(1-\theta)]$ and $\frac{\partial P_2^*}{\partial \sigma} = \frac{4\sigma k_2 \theta^2 A_1^2}{(A_1 A_2)^2}(c_2 - a_0\theta)$. Therefore,

$\frac{\partial P_1^*}{\partial \sigma} > 0$ if $c_1 > a_0(1-\theta)$ and $\frac{\partial P_2^*}{\partial \sigma} > 0$ if $c_2 > a_0\theta$. (Q.E.D.)

(iii) When $\theta = 0$ *or* 1,

a) When $\theta = 1$ and $\lambda > 0$, it is obtained that

$$\frac{\partial P_1^*}{\partial \sigma} = \frac{4\sigma}{\left[A_1 A_2 - \lambda^2\right]^2}\left\{-\lambda^2 k_2 T_1 c_1 + \lambda k_2 \left(A_1 - \lambda^2\right)c_2 - a_0 \lambda k_2 A_1\right\},$$

$\frac{\partial P_2^*}{\partial \sigma} = \frac{4\sigma}{\left[A_1 A_2 - \lambda^2\right]^2}\left\{-k_2 A_1 \lambda T_1 c_1 + k_2 A_1 \left(A_1 - \lambda^2\right)c_2 - a_0 k_2 A^2{}_1\right\}$; Therefore, $\frac{\partial P_1^*}{\partial \sigma} > 0$

and $\frac{\partial P_2^*}{\partial \sigma} > 0$ if $c_2 > \frac{(\lambda T_1 c_1 + a_0 A_1)}{\left(A_1 - \lambda^2\right)} = OT_2$.

When $\theta = 0$ and $\lambda > 0$, it is found that

$$\frac{\partial P_1^*}{\partial \sigma} = \frac{4\sigma}{\left[A_1 A_2 - \lambda^2\right]^2}\left\{k_1 A_2 \left(A_2 - \lambda^2\right)c_1 - k_1 A_2 \lambda T_2 c_2 - a_0 k_1 A^2{}_2\right\},$$

$\frac{\partial P_2^*}{\partial \sigma} = \frac{4\sigma}{\left[A_1 A_2 - \lambda^2\right]^2}\left\{\lambda k_1 \left(A_2 - \lambda^2\right)c_1 - \lambda^2 k_1 T_2 c_2 - a_0 \lambda k_1 A_2\right\}$. Therefore, $\frac{\partial P_1^*}{\partial \sigma} > 0$ and

$\frac{\partial P_2^*}{\partial \sigma} > 0$ if $c_1 > \frac{(\lambda T_2 c_2 + a_0 A_2)}{\left(A_2 - \lambda^2\right)} = OT_1$. (Q.E.D.)

b) When $\theta = 1$ and $\lambda = 0$, it is obtained that $\frac{\partial P_1^*}{\partial \sigma} = 0$, and $\frac{\partial P_2^*}{\partial \sigma} > 0$ if $c_2 > a_0$;

When $\theta = 0$ and $\lambda = 0$, it is found that $\frac{\partial P_2^*}{\partial \sigma} = 0$, and $\frac{\partial P_1^*}{\partial \sigma} > 0$ if $c_1 > a_0$.

(Q.E.D.)

Extended analyses

Proof of Lemma 2**.** Checking the second-order derivatives of **Eq.** (4-16), it is found that $\frac{\partial^2 O_1^e}{\partial (P_1^e)^2} = -2 - 2S_1k_1 - 2\delta^2 k_1 < 0$ and $\frac{\partial^2 O_2^e}{\partial (P_2^e)^2} = -2 - 2S_2k_2 - 2\delta^2 k_2 < 0$, which proves that both objective functions are concave in the respective unit price. Consequently, the reactive functions for the two players could be identified through solving the first-order conditions as follows:

$$P_1^e = \arg_{P_1}\left\{\frac{\partial O_1^e}{\partial P_1^e} = 0\right\} \longrightarrow P_1^e / P_2^e = \frac{(1-\theta)a_0[1+2k_1\delta^2] + \lambda P_2^e[1+2k_1\delta^2] + c_{10}(1+2S_1k_1)}{2(1+S_1k_1+k_1\delta^2)}$$

$$P_2^e = \arg_{P_2}\left\{\frac{\partial O_2^e}{\partial P_2^e} = 0\right\} \longrightarrow P_2^e / P_1^e = \frac{\theta a_0(1+2k_2\delta^2) + \lambda P_1^e(1+2k_2\delta^2) + c_{20}(1+2S_2k_2)}{2(1+S_2k_2+k_2\delta^2)}$$

Solving the reactive functions, the optimal prices for the two carriers could be obtained for the extended model. Besides, $B_1B_2 > \lambda^2\eta_1\eta_2$ always holds. (Q.E.D.)

Proof of Proposition 5

Checking the first order derivatives of P_1^{e*} and P_2^{e*} with respect to δ, it is found that:

$$\frac{\partial P_1^{e*}}{\partial \delta} = \frac{4\delta}{\left[B_1B_2 - \lambda^2\eta_1\eta_2\right]^2}\left\{\begin{array}{l}[k_2\lambda^2\eta_1(B_2-\eta_2) - k_1B_2(B_2-\lambda^2\eta_2)](1+2S_1k_1)c_{10} + \lambda[k_1B_2(B_1-\eta_1) - k_2\eta_1(B_1-\lambda^2\eta_1)](1+2S_2k_2)c_{20} \\ +[k_2\lambda^2\eta_1(B_2-\eta_2) - k_1B_2(B_2-\lambda^2\eta_2)](1-\theta)a_0\eta_1 + \lambda[k_1B_2(B_1-\eta_1) - k_2\eta_1(B_1-\lambda^2\eta_1)]\theta a_0\eta_2 \\ +[(1-\theta)a_0k_1B_2 + \lambda k_2\eta_1\theta a_0](B_1B_2 - \lambda^2\eta_1\eta_2)\end{array}\right\}$$

, and

$$\frac{\partial P_2^{e*}}{\partial \delta} = \frac{4\delta}{\left[B_1B_2 - \lambda^2\eta_1\eta_2\right]^2}\left\{\begin{array}{l}[k_1\lambda^2\eta_2(B_1-\eta_1) - k_2B_1(B_1-\lambda^2\eta_1)](1+2S_2k_2)c_{20} + \lambda[k_2B_1(B_2-\eta_2) - k_1\eta_2(B_2-\lambda^2\eta_2)](1+2S_1k_1)c_{10} \\ +[k_1\lambda^2\eta_2(B_1-\eta_1) - k_2B_1(B_1-\lambda^2\eta_1)]\theta a_0\eta_2 + \lambda[k_2B_1(B_2-\eta_2) - k_1\eta_2(B_2-\lambda^2\eta_2)](1-\theta)a_0\eta_1 \\ +[\theta a_0k_2B_1 + \lambda k_1\eta_2(1-\theta)a_0](B_1B_2 - \lambda^2\eta_1\eta_2)\end{array}\right\}.$$

Besides, it is identified that $B_r - \eta_r = 1 + 2S_rk_r \geq 1$ and

$\lambda^2\eta_r - B_r = (\lambda^2 - 2) + (\lambda^2 - 1)2k_r\delta^2 - 2S_rk_r < 0$.

(i) When $\lambda > 0$, let $\vartheta_1 = \frac{\lambda^2\eta_1(B_2-\eta_2)}{B_2(B_2-\lambda^2\eta_2)}$, $\varsigma_2 = \frac{B_2(B_1-\eta_1)}{\eta_1(B_1-\lambda^2\eta_1)}$, $\vartheta_2 = \frac{\lambda^2\eta_2(B_1-\eta_1)}{B_1(B_1-\lambda^2\eta_1)}$, $\varsigma_1 = \frac{B_1(B_2-\eta_2)}{\eta_2(B_2-\lambda^2\eta_2)}$

a) For carrier 1, when $\tau_1 > \vartheta_1$, when c_{10} is sufficiently small, that is,

$$c_{10} < \frac{\begin{array}{l}[k_2\lambda\eta_1(B_1-\lambda^2\eta_1) - k_1B_2\lambda(B_1-\eta_1)]B_4 + [k_1B_2(B_2-\lambda^2\eta_2) - k_2\lambda^2\eta_1(B_2-\eta_2)](1-\theta)a_0\eta_1 \\ -[(1-\theta)a_0k_1B_2 + \lambda k_2\eta_1\theta a_0](B_1B_2 - \lambda^2\eta_1\eta_2)\end{array}}{[k_2\lambda^2\eta_1(B_2-\eta_2) + k_1B_2(\lambda^2\eta_2 - B_2)](1+2S_1k_1)} = WT_1,$$

then it is identified that $\frac{\partial P_1^{e*}}{\partial \delta} > 0$.

For carrier 2, if $\tau_2 > \vartheta_2$, if c_{20} is sufficiently small, that is,

$$c_{20} < \frac{\begin{array}{c}[k_1\lambda\eta_2(B_2-\lambda^2\eta_2)-k_2B_1\lambda(B_2-\eta_2)]B_3+[k_2B_1(B_1-\lambda^2\eta_1)-k_1\lambda^2\eta_2(B_1-\eta_1)]\theta a_0\eta_2\\ -[\theta a_0k_2B_1+\lambda k_1\eta_2(1-\theta)a_0](B_1B_2-\lambda^2\eta_1\eta_2)\end{array}}{[k_1\lambda^2\eta_2(B_1-\eta_1)+k_2B_1(\lambda^2\eta_1-B_1)](1+2S_2k_2)} = WT_2$$

, then it is obtained that $\frac{\partial P_2^{e*}}{\partial \delta} > 0$. (Q.E.D.)

b) For carrier 2, when $\tau_1 > \varsigma_1$, when c_{10} is sufficiently small, that is,

$$c_{10} < \frac{\begin{array}{c}[k_2B_1(B_1-\lambda^2\eta_1)-k_1\lambda^2\eta_2(B_1-\eta_1)]B_4+[k_1\lambda\eta_2(B_2-\lambda^2\eta_2)-k_2B_1\lambda(B_2-\eta_2)](1-\theta)a_0\eta_1\\ -[\theta a_0k_2B_1+\lambda k_1\eta_2(1-\theta)a_0](B_1B_2-\lambda^2\eta_1\eta_2)\end{array}}{[k_2B_1\lambda(B_2-\eta_2)+k_1\lambda\eta_2(\lambda^2\eta_2-B_2)](1+2S_1k_1)} = UT_1,$$

then it is identified that $\frac{\partial P_2^{e*}}{\partial \delta} > 0$.

For carrier 1, when $\tau_2 > \varsigma_2$, if c_{20} is sufficiently small, that is,

$$c_{20} < \frac{\begin{array}{c}[k_1B_2(B_2-\lambda^2\eta_2)-k_2\lambda^2\eta_1(B_2-\eta_2)]B_3+[k_2\lambda\eta_1(B_1-\lambda^2\eta_1)-k_1B_2\lambda(B_1-\eta_1)]\theta a_0\eta_2\\ -[(1-\theta)a_0k_1B_2+\lambda k_2\eta_1\theta a_0](B_1B_2-\lambda^2\eta_1\eta_2)\end{array}}{[k_1B_2\lambda(B_1-\eta_1)+k_2\lambda\eta_1(\lambda^2\eta_1-B_1)](1+2S_2k_2)} = UT_2$$

, then $\frac{\partial P_1^{e*}}{\partial \delta} > 0$. (Q.E.D.)

(ii) When $\lambda = 0$,

a) When $0 < \theta < 1$, it is identified that

$\frac{\partial P_1^{e*}}{\partial \delta} = \frac{4\delta k_1B_2^2}{(B_1B_2)^2}\left\{[(1-\theta)a_0-c_{10}](1+2S_1k_1)\right\}$. Therefore, $\frac{\partial P_1^{e*}}{\partial \delta} > 0$ if

$c_{10} < (1-\theta)a_0$. Besides, $\frac{\partial P_2^{e*}}{\partial \delta} = \frac{4\delta k_2B_1^2}{\left[B_1B_2-\lambda^2\eta_1\eta_2\right]^2}\left\{(\theta a_0-c_{20})(1+2S_2k_2)\right\}$.

Therefore, $\frac{\partial P_2^{e*}}{\partial \delta} > 0$ if $c_{20} < \theta a_0$. (Q.E.D.)

b) When $\theta = 0$ or 1,

When $\theta = 1$, it is obtained that $\frac{\partial P_1^{e*}}{\partial \delta} = \frac{4\delta}{(B_1B_2)^2}[-k_1B_2^2(1+2S_1k_1)c_{10}] \le 0$. Besides,

$\frac{\partial P_2^{e*}}{\partial \delta} = \frac{4\delta k_2B_1^2}{\left[B_1B_2\right]^2}(a_0-c_{20})(1+2S_2k_2)$. Therefore, $\frac{\partial P_2^{e*}}{\partial \delta} > 0$ if $c_{20} < a_0$.

When $\theta = 0$, it is identified that $\frac{\partial P_2^{e*}}{\partial \delta} = \frac{4\delta}{(B_1 B_2)^2}[-k_2 B_1^{\ 2}(1+2S_2 k_2)c_{20}] \leq 0$.

Besides, $\frac{\partial P_1^{e*}}{\partial \delta} = \frac{4\delta k_1 B_2^{\ 2}}{(B_1 B_2)^2}(a_0 - c_{10})(1+2S_1 k_1)$. Therefore, $\frac{\partial P_1^{e*}}{\partial \delta} > 0$ if $c_{10} < a_0$.

(Q.E.D.)

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