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Individual scheduling approach for multi-class airline cabin crew with manpower requirement heterogeneity

Abstract: The cabin crew pairing problem is one of the major challenges faced by airlines. Traditionally, multi-class cabin crews are scheduled on a team basis separated by aircraft types (families) as cockpit crews. However, the manpower requirements for cabin crew across aircraft types (families) are heterogeneous, which cannot be handled by the team scheduling approach. Thus, some airlines nowadays are adopting the individual scheduling approach to deal with the flight manpower requirement heterogeneity. Motivated by the emergence of the individual cabin crew pairing practice, we conduct an analytical study which aims at improving manpower utilization while reducing costs by utilizing a new individual cabin crew pairing generation approach. We also mathematically formulate crew substitution in the model which can help hedge against manpower requirement variations. The impacts of the relationship between manpower availability with requirement benchmarks on cabin crew scheduling strategies are investigated to derive deep insights. A column generation based heuristic solution approach is developed. Computational experiments based on small-scale real-world collected flight schedules are conducted to test the distinctive features of the proposed individual pairing model. In addition, a series of large hypothetical instances are employed to examine the advantages of the proposed model over the traditional team-based model in terms of manpower utilization improvement and cost reduction through a customized Genetic Algorithm.

Keywords: Airline scheduling; Cabin crews; Column generation; Manpower requirement heterogeneity

1. Introduction

1.1 Background and Motivation

The airline industry is playing an important role in the modern world through facilitating both passenger and commodity movement nationally and internationally (Brueckner et al., 2021; Choi et al., 2019; Chung 2021; Khan et al, 2021; Wen et al. 2021). The total air passenger traffic generates 8686 billion revenue passenger-kilometres (RPKs) in 2019[1]. At the same time, the airline industry is featured with fierce competition and high operating costs (Jiang et al., 2021; Wen et al. 2020). Therefore, airlines are fully committed to improving decision quality to maintain profitability in the furiously competitive market. Airline scheduling is usually divided into four sequential stages: flight scheduling, fleet assignment, aircraft maintenance routing, and crew scheduling (Bolić et al., 2021; Liang et al. 2015, Ng et al. 2017; Woo & Moon, 2021). Some airlines also solve the airline scheduling problem in less than three stages. Among these problems, crew scheduling is an important but challenging task which assigns crews to serve the scheduled flights with the minimum cost (Barnhart and Cohn 2004; Desaulniers et al. 1997; Quesnel et al. 2020). Crew scheduling is further divided into a crew pairing

[1] https://www.icao.int/annual-report-2019/Pages/the-world-of-air-transport-in-2019.aspx.

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 and Barnhart 2003). Currently, there is little research studying the important cabin crew pairing problem with considerations of the distinctive characteristics of cabin crews. This paper thus focuses on improving the financial performance of cabin crew scheduling decisions with an individual management system. In the following, we firstly introduce the two-stage crew scheduling problem in Section 1.1.1, followed by the comparison between cockpit crews and cabin crews in Section 1.1.2. Next, we introduce an important practical operation of controlled crew substitution for cabin crews in Section 1.1.3. Finally, Section 1.1.4 highlights the importance of the pairing problem for cabin crews.

1.1.1 Crew scheduling: Crew pairing & crew assignment

Airlines need to generate crew schedules to cover all operating flights under a couple of rules with respect to the real world. The crew scheduling problem is generally divided into a crew pairing problem (CPP) and a crew assignment problem (CAP) (Chung et al. 2017, Doi et al. 2018, Quesnel 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, usually for a week or month. 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 (rosters) for specific crews with the consideration of crew availability and pre-scheduled activities such as training and vacations (Chung et al. 2015, Zeighami and Soumis 2019).

1.1.2 Two types of crews: Cockpit crew & cabin crew

There are two types of crews in airlines: cockpit crews and cabin crews. A cockpit crew (e.g., 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. 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 (families) of aircraft. 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 and 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 (because cabin crews can stay together throughout the pairing to build familiarity and obtain mutual support) (Farh et al. 2012; Guzzo and Dickson 1996; Xanthopoulou et al., 2008) and reducing problem complexity (e.g., less decision variables, simple flight coverage constraints) (Yan et al. 2002), it inevitably leads to low manpower flexibility and utilization, which increases operational costs. Therefore, realizing that the pairing problem for cabin crews is totally different from that for cockpit crews, the Airways[2] starts to adopt the individual pairing approach to overcome the shortcomings of the existing method. However, the problem scale and complexity of the individual cabin CPP are much higher than those of the traditional method.

1.1.3 An important cabin crew operation: Controlled crew substitution

Airlines may employ different types of aircraft to operate flights from time to time. For instance, a flight from Hong Kong to Singapore this week might employ A330, but in the next week, it might use A350. Moreover, instead of staying static, flight frequency is usually affected by the dynamic passenger demand and airline competition decisions (Hsu and Wen 2003, Vaze and Barnhart 2012). For example, based on a sample containing more than 1,000 airports, Airports Council International (ACI) reports that July and August are the most prevalent peak months for more than half of the studied airports. These two months coincide with a higher propensity to travel as it is in the summer vacation[3]. Therefore, flight schedules usually fluctuate along time either in flight frequency or in the aircraft types used (called *flight fluctuation* in the following). Accordingly, flight fluctuation could lead to a variation in the requirements for cabin crews. Due to the finite availability, cabin crew insufficiency may occur during flight fluctuation. Crew substitution is thus adopted by many airlines (e.g., the Airways). Controlled Crew Substitution (CCS) is to assign a cabin crew from another class to substitute the originally required one, with the aim of identifying feasible pairing plans when the current available manpower encounters a shortage in certain classes. 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. In this study, we allow cabin crew members from all classes to substitute others to complete their tasks. However, in many airlines, different settings may be applied, i.e., only higher-class crew members can substitute lower-class ones.

[2] This finding is based on a discussion with the managers from the Airways.
[3] https://blog.aci.aero/airport-markets-and-seasonal-variations/

1.1.4 Importance of the pairing problem for cabin crews

Cabin crews are crucial in maintaining service levels and providing 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, during the normal times (i.e., before the COVID-19 pandemic), 45.8% of the employees in the Airways are cabin crews, which is 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, 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[4]. 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 (Salazar-González 2014). However, despite the realized significance of cabin crews, relatively less research has focused on improving the decision quality of the cabin CPP compared to the cockpit CPP due to the high problem complexity. Then, we review the related literature in Section 1.2 and summarize research gaps in Section 1.3.

1.2 Literature Review

In the literature, there are four main streams of CPP: the CPP for cockpit crews only, the CPP for cockpit & cabin crews, the CPP for cabin crews only, and the CPP for general crews.

The CPP for cockpit crews only. Much of the CPP research concentrates solely on cockpit crews (e.g., Saddoune et al. 2012, Sandhu and Klabjan 2007). In these works, the CPP is decomposed by aircraft types with identical manpower configurations due to the characteristics of cockpit crews. Therefore, the challenge of flight requirement heterogeneity does not exist in the cockpit CPP. The decision variables are generally formulated for cockpit crew team pairings in which team members work together throughout the pairing, with the constraints of each flight being covered by (at least) one team. 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). Besides, Zeighami and Soumis (2019) develop a CPP and CAP integrated model for pilots and copilots, in which vacation requests are incorporated into an extension of the crew pairing problem.

The CPP for cockpit & 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, Erdoğan et al. 2015). 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. The second sub-stream, with only one piece of research (Medard and Sawhney 2007), treats the two types of crews differently. Medard and Sawhney (2007) recognize the flight requirement

[4] http://hk.on.cc/hk/bkn/cnt/news/20171217/bkn-20171217100546523-1217_00822_001.html

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 manpower availability limits.

The CPP for cabin crews only. The third stream focuses on the CPP for cabin crews, with only a few research works. First, similar to the first sub-stream of the second stream, Yan and Tu (2002) build cabin crew team pairings. Differently, Yan et al. (2002) consider the various flight requirements across aircraft types of a Taiwan airline, and uses 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 considers crew substitution. However, the crew substitution in Yan et al. (2002) is uncontrolled. Furthermore, their model ignores manpower availability constraints. Moreover, Quesnel et al. (2020) study a new variant of the crew pairing problem in which the language requirements of cabin crew members are considered (e.g., crew members who can speak certain languages shall be assigned to certain flights). Accordingly, a branch-and-price heuristic is proposed to solve the problem in Quesnel et al. (2020).

The CPP for general crews. The works in this stream apply the word of “crew”, instead of specifying “cockpit” crews or “cabin” crews (Cacchiani and Salazar-González 2017; Mercier 2008; Mercier and Soumis 2007; Papadakos 2009; Ruther et al. 2017; Wen et al. 2021). 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 the work of Sun et al. (2020), the Heteroscedastic regression model is utilized to conduct analytics on massive historical data, to identify the relationships between flight flying times and flight departure times. Interestingly, the authors find that the flights departing during peak times are more possible to encounter a shortened flying time to compensate the delay during departure. Based on these findings, a new robust crew pairing approach is proposed, which can minimize the differences between the scheduled flight departure times and the predicted flight departure times for all flights. Similarly, Wen et al. (2020) propose a new robust crew pairing approach which aims to promote the creation of pairings in which flights are less possibly influenced by the predicted delay of previous flights. In this stream of studies, the distinctive characteristics of cabin crews are not considered.

1.3 Research Gaps

From the discussion above, several research gaps could be obtained: First, cabin crews are studied much less than cockpit crews in the CPP literature. Second, 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. Third, little literature deals with the heterogeneity of flights in terms of the requirements for multi-class cabin crews. Fourth, there is no literature integrating the availability constraint for each class of cabin crews into the CPP. Fifth, the airline practical operation of CCS is rather underexplored in the literature. Last, to the best of our knowledge, no study analyzes the impacts of the relationship between cabin crew availability with manpower requirement benchmarks on cabin crew management in the literature. Briefly, 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 be benefited from bridging these gaps to mitigate the deficiencies of the existing methodologies.

1.4 Contribution Statements

Realizing the research gaps in the literature and the real problems revealed from some airline practices, this work proposes a novel individual pairing generation methodology for multi-class cabin crews (named as *Multi-class individual cabin crew pairing problem with availability and controlled crew substitution* (MICCPP-ACCS)). A column generation based heuristic solution approach is constructed. To better satisfy the heterogeneous flight requirements of various aircraft types (families), 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 flight manpower requirement heterogeneity on the cabin CPP, which underlies the modelling and analysis of this work. Note that the planning horizon considered in this study is a week.

Through computational experiments based on small-scale instances, the distinctive features of MICCPP-ACCS are examined (e.g., flight manpower requirement benchmarks, diverse manpower availability-requirement scenarios, and effects of CCS). In addition, we apply a series of large hypothetical instances to examine the advantages of MICCPP-ACCS over TCCPP. To improve the comparability of the traditional model and MICCPP-ACCS, we consider two categories of traditional model: One is consistent with the existing literature without manpower availability constraints, and the other is with limited available manpower. It is shown that MICCPP-ACCS can significantly reduce manpower waste (thus improving cabin crew utilization), compared to the traditional model with and without manpower availability restrictions. In the tested instances, MICCPP-ACCS can even eliminate idle crews (that is, manpower waste). Besides, MICCPP-ACCS shows great potential in reducing operating costs. Consequently, the significance of the individual scheduling approach and controlled crew substitution for airline cabin crews are highlighted.

2. Problem Description

This section 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, we introduce the definitions regarding the cabin CPP. 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, which highlights the significance of individual scheduling. Lastly, we introduce the principles and mechanisms of CCS.

2.1 Definitions

Given a flight schedule containing the information regarding flight departure / arrival airports, flight departure /arrival times, and 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[5]. 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 (idle crews) for repositioning to an airport where they are required to operate duties. This type of flights is called *deadhead* (Yan and 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). We apply the TAFB to represent the pairing cost in this study[6]. In the following, we call the pairings for individual cabin crews considered in the current work 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.

2.2 Duty-based Networks

In this section, we build flight networks for pairing generation. 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. In a flight-based network, each intermediate node stands for a flight, while in a duty-based network, intermediate nodes represent duties. In order to build a duty-based network, flights are firstly connected to form duties according to the duty-related regulations (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 as some regulations are already considered during the network construction process (Vance et al. 1997). Hence, we utilize the duty-based network in this work.

Network construction. Here, we construct 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 1**). We use s (source node) and k (sink node) to represent the home base. Note that all possible duties are built for the network development. Besides, the networks for each class are identical since the working rules are the same. Therefore, we only need to develop the network for one class, which is applicable to others. First of all, flights ($i \in F$) are connected to form duty

[5] We employ the aviation terminologies from Belobaba et al. (2015), 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.

[6] Note that different airlines may apply different cost structures, like duty costs, rest costs, deadhead costs, etc. In this study, to focus on the impact of individual scheduling approach and controlled crew substitution, we simply apply the TAFB as the pairing cost.

nodes ($d_m^r \in D_r$). Note that one flight could appear in more than one duty in the network (because a flight could be connected with different flights to form different duties). A typical duty is illustrated in the upper right corner of **Figure 1**. Deadhead arcs are parallel to flight legs. Then, the constructed duty nodes are linked by rest arcs (i.e., $(d_{m_1}^r, d_{m_2}^r)$). All duties starting from the home base are connected with the source node (s) through starting arcs (i.e., (s, d_m^r)), while those ending at the home base are linked with the sink node (k) through ending arcs (i.e., (d_m^r, k)).

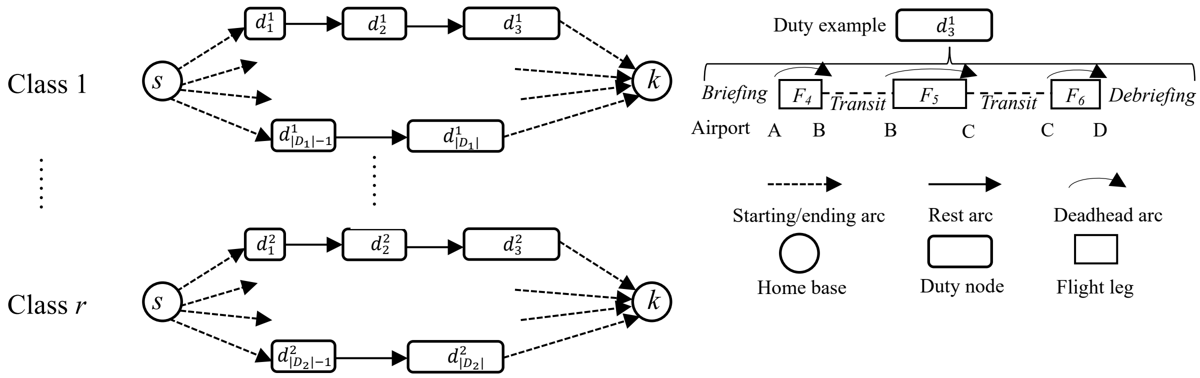

Figure 1. Typical duty-based networks for multi-class cabin crews.

2.3 Flight Requirement Heterogeneity

In this part, we discuss 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 2**, in which three flights, Flights 7, 8, and 9 (i.e., F7, F8, and F9) can form three duties: d_4^1 (F7 and F9), d_5^1 (F8), and d_6^1 (F8 and F9). It is seen that F9 is included in two duties (d_4^1 and d_6^1). Three potential pairings could cover these three duties: Pairing 1 contains d_4^1 (F7 and F9), Pairing 2 covers d_5^1 (F8), while Pairing 3 includes d_6^1 (F8 and F9). Therefore, if we would like to cover all flights by selecting these three potential pairings, two pairing combination options are available: Pairings 1+2, and Pairings 1+3. The three flights have heterogeneous manpower requirements. We denote the number of Class r cabin crews required by flight i as b_i^r. Specifically, F7 and F8 demand only one ($b_7^1 = b_8^1 = 1$), while F9 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 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, cabin crews are modelled as teams. Therefore, both Team Pairing 1 and Team Pairing 3 should be assigned with two cabin crews as F9 needs two, while Team Pairing 2 only requires one cabin crew. As a result, to cover all the three flights' manpower requirements using the team modelling approach, a minimum of three cabin crews are needed (the combination of Team Pairings 1+2 is selected; Two cabin crews are for Team Pairing 1, and one is for Team Pairing 2). Here, one cabin crew assigned to Team Pairing 1 is idle on F7 (causing a manpower waste). 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 cabin crews (the combination of Individual Pairings 1+3 is selected; One cabin crew is for Individual Pairing 1, and one is 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 idle. 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.

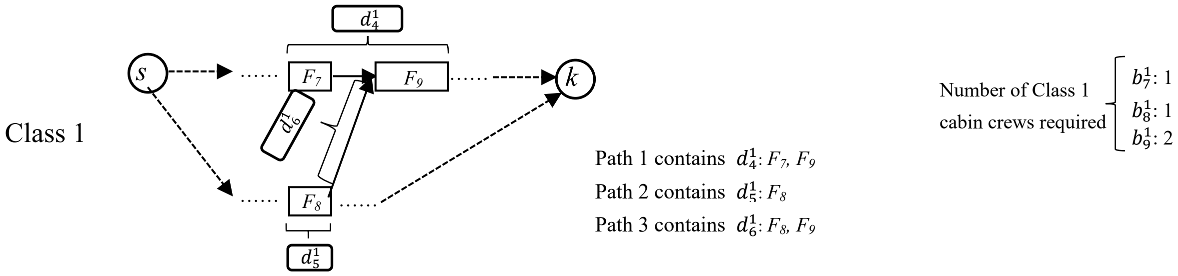

Figure 2. An example of flight manpower requirement heterogeneity based on Class 1.

2.4 Controlled Crew Substitution

With finite availability, cabin crews of some classes may be insufficient to cover all flights during flight fluctuation. To deal with this problem, the Airways applies the strategy of CCS to utilize cabin crews from other classes (*substituter*) to substitute the originally required ones (*substitutee*)[7]. Note that crew substitution is under control for the purpose of facilitating normal flight operations, instead of saving costs. With this strategy, if sufficient cabin crews of all classes that are no less than the total requirements of the flight are assigned to a flight, the normal operation of this flight is not disrupted no matter which specific class is insufficient. This condition is called the *total satisfaction constraint*. We denote the number of Class r cabin crews assigned to flight i 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 Eq. (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 in this current study, we allow cabin crew members from all

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

classes to substitute others to complete their tasks. However, in many airlines, different settings are commonly seen, i.e., only higher-class crew members can substitute lower-class ones.

$$\sum_{r\in R} q_i^r \geq \sum_{r\in R} b_i^r, \qquad \forall i \in F. \tag{1}$$

On the other hand, regulations in the Airways also specify that at least one qualified cabin crew from each class should be assigned to each flight (called the *minimum satisfaction constraint*), as in Eq. (2).

$$q_i^r \geq 1, \qquad \forall i \in F,\ \forall r \in R. \tag{2}$$

A simple example of CCS is illustrated in **Figure 3**. In the example, we consider 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 idle 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 will 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.

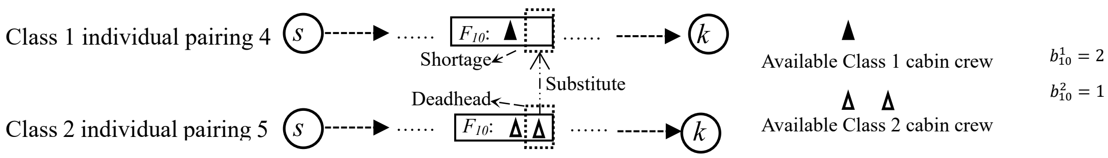

Figure 3. A simple example of CCS.

3. Mathematical Formulations

In this section, we first briefly review the traditional models in the literature. Next, the proposed MICCPP-ACCS is formulated, followed by the simplified version MICCPP-A.

3.1 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 associated with an aircraft type. j_t is applied to stand for the team pairing, while J_t is the set of potential team pairings for cabin crews. The binary decision variable x_{j_t} represents whether the team pairing $j_t \in J_t$ is selected or not. 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.

$$\text{(TCCPP)} \quad \text{Min} \quad \sum_{j_t \in J_t} c_{j_t} x_{j_t} \tag{3}$$

$$\text{s.t.} \quad \sum_{j_t \in J_t} a_{ij_t} x_{j_t} \geq 1, \qquad \forall i \in F, \tag{4}$$

$$x_{j_t} = 0 \text{ or } 1, \qquad \forall j_t \in J_t. \tag{5}$$

The objective Eq. (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. (4), requiring that each flight is covered by at least one team. Following the mainstream CPP literature (e.g., Erdoğan et al. 2015), the manpower availability limitation is not considered in TCCPP. Therefore, TCCPP is inclined to generate many short pairings to minimize the TAFB pairing cost[8]. 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. More importantly, the flexibility and utilization of cabin crews are greatly impaired.

3.2 The Proposed MICCPP-ACCS

This section 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. (6) to Eqs. (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. 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 coefficients 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.

$$\text{(MICCPP-ACCS)} \quad \text{Min} \quad \sum_{r \in R} \sum_{j_r \in J_r} c_{j_r} x_{j_r} + \sum_{r \in R} \sum_{i \in F} \mu s_i^r + \sum_{r \in R} \sum_{j_r^e \in J_r^e} (c_{j_r^e} + M) x_{j_r^e} \tag{6}$$

$$\text{s.t.} \quad \sum_{r \in R} \sum_{j_r \in J_r} a_{ij_r} x_{j_r} + \sum_{r \in R} \sum_{j_r^e \in J_r^e} a_{ij_r^e} x_{j_r^e} \geq \sum_{r \in R} b_i^r, \qquad \forall i \in F, \tag{7}$$

$$\sum_{j_r \in J_r} a_{ij_r} x_{j_r} + \sum_{j_r^e \in J_r^e} a_{ij_r^e} x_{j_r^e} \geq 1, \qquad \forall i \in F, \forall r \in R, \tag{8}$$

[8] Note that as we use the TAFB to represent the pairing cost, which is a simplified version of the complex non-linear type pairing cost.

$$\sum_{j_r \in J_r} a_{ij_r} x_{j_r} + \sum_{j_r^e \in J_r^e} a_{ij_r^e} x_{j_r^e} + s_i^r \geq b_i^r, \qquad \forall i \in F, \forall r \in R, \qquad (9)$$

$$\sum_{j_r \in J_r} x_{j_r} \leq d_r, \qquad \forall r \in R, \qquad (10)$$

$$x_{j_r} = \text{ non-negative integer}, \qquad \forall r \in R, \forall j_r \in J_r, \qquad (11)$$

$$x_{j_r^e} = \text{ non-negative integer}, \qquad \forall r \in R, \forall j_r^e \in J_r^e, \qquad (12)$$

$$s_i^r = \text{ non-negative integer}, \qquad \forall i \in F, \forall r \in R. \qquad (13)$$

In MICCPP-ACCS, the available cabin crews are always the first resource to be selected to satisfy the flights scheduled. Once any class encounters a manpower shortage during flight fluctuation, CCS will identify cabin crews from other classes to fill the vacancy. We introduce extra cabin crew variables to ensure solution feasibility. In practice, airlines can employ temporary cabin crews and part-time cabin crews as extra manpower.

The minimization objective function Eq. (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; iii) sum of the costs of extra cabin crews introduced which further consists of the pairing cost $c_{j_r^e}$ and a big penalty value M[9]. 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. (7) as group 1, Eqs. (8) and Eqs. (9) as group 2, Eqs. (10) as group 3, and Eqs. (11) to (13) as group 4.

The first group (Eqs. (7)) concerns flight coverage and crew substitution, which is equivalent to Eq. (1). Specifically, the right-hand side of each row in Eqs. (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 Eq. (1)). Therefore, Eqs. (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. (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 ($x_{j_r^e}$). 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. (7) is controlled by the second group of constraints. First, Eqs. (8) represent the minimum satisfaction constraint (as discussed in Section 2.4, Eq. (2)), to allocate at least one qualified cabin crew from the required class to each flight. The left-hand side of each row in Eqs. (8) is the total number of Class r cabin crews assigned to the flight (i.e., q_i^r). Second, Eqs. (9) play a pivotal role in avoiding unnecessary substitutions. In particular, each row of Eqs. (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

[9] For the part of extra cabin crews in the objective function (Eq. (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.

least-cost 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 for a certain class on a flight, 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 duties, will the model turn to extra cabin crews to identify feasible solutions.

The third group (Eqs. (10)) puts an upper limit on the number of individual pairings that can be generated for each class of available cabin crew within a week time period. Each individual pairing requires a cabin crew to operate. Therefore, in this study, we apply the number of individual pairings as a rough approximation on the workforce requirement. Accordingly, in this work, these restrictions (Eqs. (10)) are termed as “crew availability constraints”. Besides, these availability constraints are not hard constraints, as extra manpower is allowed with a penalty.

The last group (Eqs. (11) to (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 4. 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. We describe the calculation procedure as follows. First, the number of available cabin crew for each class is set as zero (that is, all d_r are 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., $\sum_{r \in R} \sum_{j_r^e \in J_r^e} x_{j_r^e}$) is thus the MS for the flight schedule.

3.3 The Simplified MICCPP-A

In this subsection, we further propose an MICCPP-A (as shown in Eq. (14) to Eqs. (18)) which is a simplified version of MICCPP-ACCS where the strategy of CCS is forbidden. Although MICCPP-ACCS is the primary model we constructed in this work, we would like to show that the individual cabin crew pairing model for heterogeneous manpower requirements is in the format of MICCPP-A where the various cabin crew classes are scheduled independently (i.e., without the application of the CCS strategy). The objective function Eq. (14) is to minimize the total pairing cost and the big penalty cost of the employment of extra cabin crews. It is seen that compared with the MICCPP-ACCS, Eq. (14) does not involve the crew substitution penalty cost. Eqs. (15) are the flight coverage constraints to specify that for each flight, sufficient Class *r* cabin crew members (both available and extra ones) shall be allocated. Then, Eq. (16) regulates the number of the available Class *r* cabin crew members. Eqs. (17) and Eqs. (18) define the solution space of the decision variables.

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

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

$$\sum_{j_r \in J_r} x_{j_r} \leq d_r, \quad (16)$$

$$x_{j_r} = \text{non-negative integer}, \quad \forall j_r \in J_r, \quad (17)$$

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

Table 1. 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		√	√				$\|F\|$	1
MICCPP-ACCS	√			√	√	√	$(2\|R\|+1) \times \|F\| + \|R\|$	$\|R\|$
MICCPP-A	√			√	√		$\|F\|+1$	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 the minimum-(pairing)cost set of individual pairings to satisfy all flight requirements of this class, under a certain level of availability. **Table 1** summarizes the comparisons among TCCPP, MICCPP-ACCS, and MICCPP-A. From **Table 1**, we can see that the complexity of MICCPP-ACCS is much larger than MICCPP-A and TCCPP.

Furthermore, two important flight schedule manpower requirement benchmarks could be obtained from MICCPP-A. Note that although they can also be obtained from MICCPP-ACCS, we utilize MICCPP-A to demonstrate them in a clearer way because these two benchmarks both relate to a specific Class *r*, rather than 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 by at least 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 (as only $x_{j_r^e}$ exists in the MICCPP-A model when d_r is zero). For MM_r, all flight manpower requirements are arbitrarily set as one (setting b_i^r $(\forall i \in F)$ as 1) in the MICCPP-A model, to simulate the minimum satisfaction situation (i.e., each flight is covered by once). Similarly, no available cabin crew is applied (setting d_r as 0), so that the algorithm will only use extra cabin crews to fulfil the minimum satisfaction constraint with big penalty costs. After solving this 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. It is noted that the MM_r values for all classes are the same regarding a flight schedule. **Table 2** 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 4.

Table 2. The three flight requirement benchmarks for a flight schedule.

Benchmarks	Full name of the benchmark	Dimension	Obtained from		Parameter setting	
			MICCPP-ACCS	MICCPP-A	d_r	b_i^r
$MS = \sum_{r \in R} \sum_{j_r^e \in J_r^e} x_{j_r^e}$	*minimum total manpower demand with CCS*	For all classes	√		0	b_i^r
$MC_r = \sum_{j_r^e \in J_r^e} x_{j_r^e}$	*minimum manpower demand for Class r without CCS*	For Class *r*		√	0	b_i^r
$MM_r = \sum_{j_r^e \in J_r^e} x_{j_r^e}$	*minimum satisfaction constraint manpower demand for Class r*	For Class *r*		√	0	1

4. Manpower Availability-Requirement Analysis

Applying the proposed MICCPP-ACCS, this section presents analyses about the relationship between cabin crew availability levels and the obtained flight schedule manpower requirement benchmarks, in order to derive some managerial insights for airline cabin crew management. First of all, we recall the three manpower requirement benchmarks built for a flight schedule in Section 3: 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). We use TA 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**. Detailed explanations for each scenario are illustrated as follows. In the following discussions, we use R^* to represent the set of classes where $d_r < MM_r$. Subsets R^1, R^2, R^3, R^4 and R^5 that are used for analysis are defined in **Table 3**.

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

Availability-requirement relationship	Scenario	Implications on manpower management

<table>
<tr><th>First-layer (A)</th><th>Second-layer (B)</th><th colspan="2">Third-layer (C)</th><th></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, 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 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 $\text{Max}\{\sum_{r \in R^*}(MM_r - d_r), (MS - TA)\}$ 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. **<u>Scenario 5</u>** [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. **<u>Scenario 6</u>** [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. **<u>Scenario 7</u>** [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 from other classes with the strategy of CCS due to the fact that $MM_r < MC_r$ (for $r \in R^5$).

B4. **<u>Scenario 8</u>** [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.

Table 4. 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	$\text{Max}\{\sum_{r\in R^*}(MM_r - d_r), (MS - TA)\}$	$\sum_{r\in R^2}(MC_r - d_r)$		√
3	$\sum_{r\in R}(MC_r - d_r)$	$\sum_{r\in R}(MC_r - d_r)$	√	
4	$\text{Max}\{\sum_{r\in R^*}(MM_r - d_r), (MS - TA)\}$	$\sum_{r\in R}(MC_r - d_r)$		√
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 $MM_r = MC_r$.

In conclusion, the analysis in this section demonstrates that the relationship between cabin crew availability levels 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 our focus is not on the daily manpower availability at this stage, we would like 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. The summary of extra manpower demand of MICCPP-ACCS in each scenario is summarized in the second column of **Table 4**, together with the comparisons with that of MICCPP-A. The last column specifies whether CCS helps in reducing the demand for extra manpower compared to 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. By referring to the relationship as examined in this section, airlines can obtain the knowledge regarding whether their available manpower is sufficient or not, and what crew planning strategy can be used.

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, $MM_r = MC_r$).

5. Solution Approach

In the literature, the continuous relaxation of the CPP is generally solved by Column Generation (CG) (e.g., Lavoie et al. 1988), a popular continuous optimization technique that can solve linear programming problems without the difficulty of explicitly considering all potential columns (Barnhart et al. 1998, Desrosiers and Lübbecke 2005, 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. As the solutions obtained from CG are not necessarily integer, branch-and-bound is always applied to get integer solutions. The overall solution methodology is thus called branch-and-price. Branching could be made according to the follow-on strategy. Diving column fixing is also commonly seen. In this study, we directly apply Mixed Integer Programming (MIP) on the columns involved in the last RMP to obtain integer solutions. This solution approach is called CG+MIP. Note that as integer solutions are obtained based on the last RMP, this approach is then a "heuristic approach", rather than a "globally optimal exact solution" approach. We describe the details of the proposed CG+MIP as follows.

5.1. Restricted Master Problem

The RMP is the linear relaxation of MICCPP-ACCS by relaxing the nonnegative-integer constraints Eqs. (11) to (13) into non-negative restrictions. Due to the limitation of available cabin crews (that is, Eqs. (10)), it is difficult to identify an initial feasible solution using the available manpower, especially when some classes are insufficient. Herein, we propose an efficient tailored initiation methodology called the *dynamic programming based initialization algorithm* (DPIA), 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 5** 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. Therefore, the RMP is initiated by inserting the variables $x_{j_r^e}$ ($j_r^e \in Q$) and corresponding columns into the pool, which is solved by the Simplex method. The dual prices associated with each constraint are then passed to the PP.

Table 5. Dynamic programming based initialization algorithm (DPIA).

```
Begin
    U ={(s)}, O = ∅, Q = ∅;
    While |O| ≠ |F|, do
    Begin
        Select the last element L ∈ U, and delete it from U;
        Extend L to all possible directions if no resource (τ ∈ Θ) is violated;
        For each newly generated (partial) path H, do
        Begin
            If H ends at the sink node k, 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
```

5.2 Pricing Problem

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

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

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

For $\bar{c}_{j_r}$, 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 Class *r*, which is unrelated with j_r. For $x_{j_r^e}$, $\bar{c}_{j_r^e}$ is similar to $\bar{c}_{j_r}$, 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 $\mu - \theta_i^r$. The pricing problem is then transformed to solving a resource constrained shortest path problem (RCSPP) in each class of duty-based network to identify new pairings with negative reduced costs. The "resources" are the legal requirements regulated by airlines, labor unions, and governments, like the maximum allowed pairing elapse time and the maximum allowed flight legs in a pairing. To address the RCSPPs, we follow the dynamic programming solution approach (also named as the labelling algorithm) described in Irnich and Desaulniers (2005). A label can be regarded as a partial path reaching a certain node, featured by the related cost and resource consumptions. Note that the resource consumptions should respect the resource window at each node. As we apply the duty-based network in this study, the resource consumptions for each duty node should be calculated according to the flights contained in the duty. For example, if a duty involves two flights, then the working time consumed by this duty node is the sum of the flight periods of these two flights plus briefing and de-briefing. Starting from the trivial initial label only containing the source node, resource-feasible source-sink paths are generated by extending the labels. The path extension step follows the label correcting algorithm (Ahuja et al. 1988; Yan and Chang 2002). To avoid enumerating all possible pairings contained in the flight networks, we apply dominance checks at each node to remove the dominated labels. That is, for two labels (i.e., two partial paths reaching the same node), if the first label incurs a lower cost and consumes fewer resources than the second, then the second label is dominated by the first, and can be removed for further consideration. Note that if two labels incur the same cost and consume the same resources, one of them should be kept. 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. Finally, we apply the MIP technique to obtain integer solutions based on the last RMP.

6. Computational Experiments

This section demonstrates the superior performance of the proposed MICCPP-ACCS model through computational experiments. 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 and MIP are solved using CPLEX Concert Technology in IBM ILOG CPLEX Optimization Studio (Version 12.6.3). The computational experiments are divided into two parts as follows.

First of all, to analyze the flight manpower requirement benchmarks and the diverse manpower availability-requirement scenarios to demonstrate the distinctive feature of MICCPP-ACCS, we conduct computational experiments based on a set of small real-world collected flight networks in Section 6.1. The proposed CG+MIP solution approach is applied to solve these small-scale instances.

Second, to examine the advantages of the proposed MICCPP-ACCS over TCCPP, we conduct computational experiments based on a series of large hypothetical and real instances with an increasing size in Section 6.2. Here, as the CG+MIP approach is not able to solve large-scale instances efficiently, we thus employ a Genetic Algorithm to obtain solutions within reasonable computation times.

6.1 Feature Analysis based on Small-scale Instances

Section 6.1.1 introduces the characteristics of the tested small instances. In Section 6.1.2, the crucial flight manpower requirement benchmarks and the diverse manpower availability-requirement scenarios are explored. Then, the critical effects of CCS on cabin crew pairing are examined in Section 6.1.3.

6.1.1 Characteristics of the Small Instances

The selected schedules & Flight fluctuation. In this section, we test the features of MICCPP-ACCS using a set of small-scale instances based on the Airways. There are four classes ($|R|$=4) of cabin crews working at the Airways. The aviation rules and regulations for pairing generation are described in Online Appendix 1. The tested instances are derived from the weekly flight schedules of the Airways. Specifically, we select eight weekly schedules (from 19, Nov 2017 to 13, Jan 2018) of a route between the home base Hong Kong (HKG) and Singapore (SIN). Each week of schedule is an independent instance. Five aircraft types are involved, denoted as Type 1, Type 2, Type 3, Type 4, and Type 5 respectively. 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 features of the eight weekly flight schedules are summarized in Table S2 of Online Appendix 2. The details of cabin layouts, seat capacities, and cabin crew requirements are illustrated in Table S3 and Table S4 (see Online Appendix 2). Regarding the value of μ and M, as the maximum TAFB pairing cost ($c_{j_r}, c_{j_r^e}$) is 7200 (as the maximum allowed TAFB for a pairing is 7200 minutes (Online Appendix 1)), we set μ as 50000 to ensure $c_{j_r}, c_{j_r^e} \ll \mu$, and M as 5000000 to ensure $\mu \ll M$. We use one typical flight (Flight 636) to demonstrate flight fluctuation in **Figure 4**, with the horizontal axis representing the day of time and the vertical axis standing for the aircraft type used. The vertical axis value of zero implies that there is no flight on that day, while an integer value means that Flight 636 is operated on that day with the corresponding type of aircraft. From **Figure 4**, it is seen that flight schedules usually fluctuate along time either in flight frequency or in the aircraft types used.

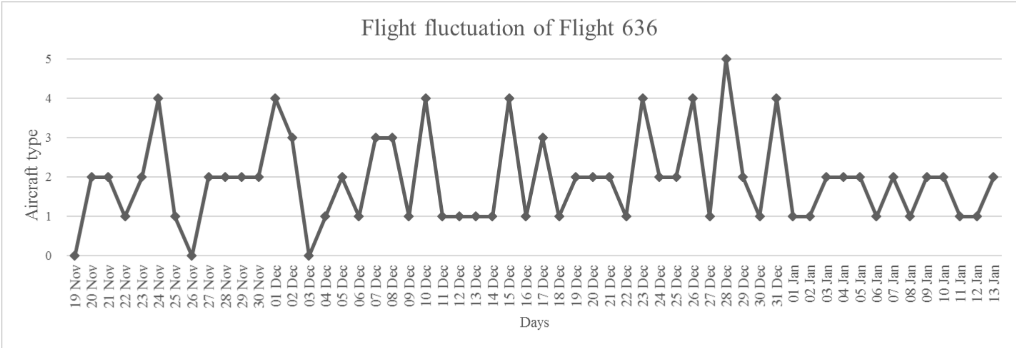

Figure 4. An example of flight fluctuation.

Preprocessing & Instances. As we consider a partial flight network, some selected flights might not appear in any pairing. Therefore, we remove those flights that cannot be covered by any feasible pairing. The processed instances (i.e., I-instance) are shown in **Table 6**.

Table 6. Characteristics of the processed small instances.

Instance	No. of flights	No. of flights operated by each type of aircraft				
		Type 1	Type 2	Type 3	Type 4	Type 5
I1	84	4	27	0	21	32
I2	85	5	29	0	23	28
I3	77	0	29	2	26	20
I4	85	18	25	0	28	14
I5	81	7	33	6	24	11
I6	77	14	33	2	14	14
I7	92	27	34	5	2	24
I8	83	21	37	2	10	13

6.1.2 Flight Requirement Benchmarks and Cabin Crew Scheduling Scenarios

Based on **Table 2**, the manpower requirement benchmarks for each I-instance are obtained as illustrated in **Table 7**, which shows the variation in the (minimum) manpower demand during flight fluctuation. For I-1 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.

Table 7. Manpower requirement benchmarks of I-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

In reality, cabin crew availability levels in airlines may vary over time due to vacations, day-offs, medical checks, training or employee turnover. We thus derive three cabin crew availability levels to test the different cabin crew scheduling scenarios led by various manpower availability-requirement relationships (as discussed in Section 4). First, the maximum value of MC_r for each class among the I-instances is selected to form Level 1 cabin crew availability (36, 42, 72, and 79 respectively, 229 totally). Second, the minimum value of MC_r for each class among the I-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 manpower requirement benchmarks, 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) to derive these two scenarios.

As discussed in Section 4, when 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. **Table 8** summarizes the scenarios corresponding to each generated availability level in each I-instance. For example, for I1 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 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. 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 under 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, $MS = \sum_{r\in R} MC_r$, 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, $d_r < MC_r$). 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 required, without the requirement for CCS (as Scenario 3). On the other hand, when Level 3 is applied to I3, 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 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 Classes 1 and 3 are higher than MC_1 and MC_3, respectively. Besides, Class 2 availability is lower than MM_2. Consequently, overall 20 extra cabin crews (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 I-instance and availability level are illustrated in Table S5 in Online Appendix 2. Besides, note that for all I-instances, MM_r is smaller than MC_r. Therefore, Scenarios 1 and 6 will not happen. We construct a set of semi-artificial instances to test the special Scenarios 1 and 6 where $MM_r = MC_r$. Details can be found in Online Appendix 3.

Table 8. Manpower availability levels and corresponding scenarios for I-instances.

Availability level					Instance - Scenario							
Index	Class 1	Class 2	Class 3	Class 4	I1	I2	I3	I4	I5	I6	I7	I8
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

The computational performances of the CG+MIP algorithm for each instance under the three manpower availability levels are summarized in **Table 9**. It is seen that for Level 1 and Level 3, the average computational times are similar (i.e., 20s on average), while for Level 2, longer times are consumed (i.e., 27s on average). Besides, most of the computation efforts are occupied by the pricing problem (i.e., running the resource shortest path problem in the flight networks of each class of cabin crew). On average, 87.8% of the total computation time is consumed by the pricing problem. Moreover, the column generation process spends the majority of the overall computation time (95%), while only 5% is used by the MIP procedure on average. Besides, the optimality gaps for all instances are around 0.01% or even zero.

Table 9. Computational performances of the CG+MIP algorithm.

Manpower availability level	Instance	Computation time (s)			
		Column generation	Pricing problem	Each iteration of PP	MIP
Level 1	I1	20.779	19.444	0.076	0.342
	I2	19.321	17.885	0.068	0.632
	I3	12.409	11.293	0.055	0.147
	I4	23.296	21.587	0.081	0.368
	I5	19.638	17.980	0.075	0.163
	I6	12.747	11.621	0.064	0.050
	I7	33.996	32.301	0.122	6.008
	I8	19.723	17.817	0.071	3.164
Average		**20.239**	**18.741**	**0.077**	**1.359**
Level 2	I1	37.666	35.391	0.157	0.527
	I2	32.749	31.010	0.130	10.019
	I3	14.782	13.687	0.078	0.210
	I4	42.613	40.475	0.172	0.990
	I5	25.105	23.235	0.107	0.494
	I6	13.637	12.493	0.083	0.868
	I7	34.040	32.041	0.135	0.873
	I8	20.047	18.145	0.086	0.328
Average		**27.580**	**25.810**	**0.119**	**1.789**
Level 3	I1	19.796	18.395	0.113	0.651

I2	18.182	16.690	0.101	0.894
I3	11.722	10.662	0.081	0.760
I4	23.485	21.854	0.135	1.776
I5	23.806	22.150	0.109	0.748
I6	8.155	7.212	0.059	0.616
I7	37.435	35.140	0.139	0.444
I8	24.131	21.604	0.095	0.296
Average	**20.839**	**19.213**	**0.104**	**0.773**

6.1.3 The Effect of CCS

In the following, we demonstrate the significant effects of CCS on cabin crews in dealing with the manpower shortage dilemma. 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 computation times of MICCPP-ACCS under the three availability levels using the CG+MIP approach are listed in Table S6 (Online Appendix 2). Specifically, the overall average computation time for I-instances is 24.193s.

The performances of CCS in I-instances are concluded in **Table 10**. The 2nd -5th and 6th -9th columns in the table show the information in terms of the CCS solutions obtained from MICCPP-ACCS under Level 2 and Level 3, respectively. The number in the 2nd -5th and 6th -9th 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. 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. Here, if CCS is not applied, the employment of an extra Class 1 cabin crew is thus necessary. 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 (thus improving manpower utilization) compared with the situation where CCS is absent.

Table 10. Performances of CCS for MICCPP-ACCS in I-instances.

Instance	CCS details - Level 2				CCS details - Level 3			
	Class 1	Class 2	Class 3	Class 4	Class 1	Class 2	Class 3	Class 4
I1	1 (F83)	2 (F73)	2 (F0, F13)	0	0	115	0	0
I2	0	1 (F84)	1 (F81)	0	0	126	0	0
I3	0	0	0	0	0	94	0	0
I4	1 (F13)	0	0	0	0	109	0	0
I5	0	1 (F53)	3 (F14, F57, F59)	0	0	11	0	6
I6	2 (F14, F27)	0	1 (F75)	0	0	70	0	0
I7	0	0	0	0	0	0	0	7
I8	0	0	0	0	0	5	0	6

6.2 Performance Analysis based on Large-scale Instances

In this section, we examine the superior performances of MICCPP-ACCS over TCCPP regarding the reduction in both manpower waste and operating cost. The tested instances involve a real instance denoted as RE, together with five hypothetical instances with an increasing size (denoted as H1 to H5). As the CG+MIP approach fails to obtain satisfactory solutions within reasonable computation times, we propose a Genetic Algorithm to deal with these large instances. Details of the Genetic Algorithm are shown in Online Appendix 4.

For each instance, we calculate the total number (arithmetic sum) of cabin crews required by all flights for each class, as shown in the third to sixth columns of **Table 11**. For example, if Flight 1 requires two Class 1, while Flight 2 requires three Class 1, then these two flights require five Class 1 cabin crews in total. For each instance, regarding the manpower availability level for each class to be tested (i.e. d_r), we apply 60%, 50%, 40%, and 30% of the total number of cabin crews required by all flights for each class.

Table 11. Characteristics of the large H-instances.

Instance	No. of flights	Total no. of cabin crews required by all flights			
		Class 1	Class 2	Class 3	Class 4
H1	154	307	389	574	650
H2	308	612	783	1146	1300
H3	616	1220	1551	2290	2597
H4	1232	2442	3098	4579	5193
H5	2002	3969	5038	7443	8440
RE	2050	4211	5524	8213	9230

According to the discussion with managers from the aviation industry, it is identified that manpower waste reduction (or manpower utilization improvement) is an important objective for them when conducting cabin crew scheduling. Higher utilization implies less manpower waste, which translates into cost reduction. Note that higher manpower utilization might not be welcomed by cabin crews due to the associated higher workload and greater fatigue. As the manpower availability constraint (Eqs. (10)) applied in this work is a rough approximation on the workforce requirement, to avoid bias in comparisons between TCCPP with MICCPP-ACCS, we define manpower waste as “the total idle time of cabin crews on all flights” and operating cost as “the total TAFB pairing cost of all pairings generated”.

Specifically, we use the total idle time of cabin crews on all flights to represent the waste of workforce. Idle crews are those who are on flights without duties. For example, on a flight, one Class 1 cabin crew and two Class 2 cabin crews fly deadhead arcs without working. Then, the total idle time of cabin crews on this flight is 3×flight period. Higher manpower waste implies lower manpower utilization. Besides, we apply the TAFB pairing cost of all pairings generated to evaluate the operating cost. In MICCPP-ACCS, the total TAFB pairing cost is the summation of the elapsed time of all the individual pairings obtained. In TCCPP, the actual TAFB pairing cost for a team pairing is the elapsed time of this team pairing multiplying the actual number of cabin crews assigned to this team. For instance, a team pairing's elapsed time is 2000, while this team contains 5 cabin crews. Then, the actual elapsed time of this team pairing is 10000. The total TAFB pairing cost for TCCPP is the summation of the actual TAFB pairing cost for all the team pairings generated.

It is noted that in the following computational experiments, we consider two categories of TCCPP to improve the comparability of TCCPP and MICCPP-ACCS. They are TCCPP-TAFB and TCCPP-Availability. TCCPP-TAFB is the traditional model using the team modelling approach with the objective of minimizing the total TAFB pairing cost (i.e., total elapsed time), as discussed in Section 3.1. As the manpower availability constraint is not considered, TCCPP-TAFB is inclined to generate many short pairings to minimize the total elapsed time. However, in our proposed MICCPP-ACCS, the available manpower is limited. Accordingly, we would also like to test the performance of TCCPP when the manpower availability restriction is integrated into the decision framework (denoted as TCCPP-Availability).

6.2.1 The Merits of MICCPP-ACCS

By applying the proposed Genetic Algorithm, all instances can reach the steady stage within 10 seconds. The solution details are summarized in **Table 12**. For TCCPP-Availability, the 60% availability level is very sufficient, as the solutions obtained from TCCPP-TAFB and TCCPP-Availability are the same in all HX/RE-60% instances. In the following, we will analyze the performances of TCCPP-TAFB, TCCPP-Availability, and our proposed MICCPP-ACCS to demonstrate the advantages of MICCPP-ACCS in improving manpower utilization and reducing operating costs.

Table 12. Model performance comparisons for the large H-instances.

Instance	Total idle time of cabin crews (in hours)			No. of extra crews required			No. of substitution for MICCPP-ACCS	Total TAFB pairing cost		
	TCCPP-TAFB	TCCPP-Availability	MICCPP-ACCS	TCCPP-TAFB	TCCPP-Availability	MICCPP-ACCS		TCCPP-TAFB	TCCPP-Availability	MICCPP-ACCS
H1-60%	640	640	0	0	0	0	0	1436190	1436190	1357675
H1-50%	626	624	0	37	12	0	0	1436190	1445885	1357675
H1-40%	640	884	0	237	15	0	0	1436190	1547015	1436260
H1-30%	562	1280	0	417	20	0	30	1436190	1657825	1521660
H2-60%	1320	1320	0	0	0	0	0	3212786	3212786	3036552
H2-50%	1330	1454	0	100	25	0	0	3212786	3272885	3036552
H2-40%	1359	1967	0	490	30	0	0	3212786	3481021	3264538
H2-30%	1239	2782	0	870	34	0	61	3212786	3840043	3409279
H3-60%	2312	2312	0	0	0	0	0	10175315	10175315	9061001
H3-50%	2659	2727	0	228	47	0	0	10175315	10309753	9061001
H3-40%	2544	3612	0	988	53	0	0	10175315	10997729	9544912
H3-30%	2428	4800	0	1758	70	0	73	10175315	11981854	9903368
H4-60%	5675	5675	0	0	0	0	0	26769392	26769392	22776437
H4-50%	5556	6247	0	479	108	0	0	26769392	27222176	22776437
H4-40%	5557	8528	0	2009	126	0	0	26769392	28662256	23705602
H4-30%	4490	8083	0	3539	791	0	163	26769392	29804992	24455257

H5-60%	9021	9021	0	0	0	0	0	48680020	48680020	40765444
H5-50%	8629	10631	0	775	0	0	0	48680020	50495733	40765444
H5-40%	8237	12230	0	2455	641	0	0	48680020	51080891	42117813
H5-30%	9609	12247	0	5765	1980	0	287	48680020	53169585	43510991
RE-60%	9318	9318	0	0	0	0	0	52282341	52282341	43741321
RE-50%	8889	12050	0	275	0	0	0	52282341	53515562	43741321
RE-40%	9751	11432	0	3097	885	0	0	52282341	54758715	45487238
RE-30%	8459	15042	0	5827	2304	0	450	52282341	56891456	46686541

Idle crews. For both TCCPP-TAFB and TCCPP-Availability, due to the deficiencies of the team modelling approach, many cabin crews remain idle on flights under all availability levels (i.e., 60%, 50%, 40%, and 30%). The total cabin crew idle time for each instance by using TCCPP is shown in the 2nd and 3rd columns of **Table 12**. As discussed in Section 2.2, the low manpower utilization in TCCPP is because cabin crews are bundled together as teams to fly all flights on that pairing with low flexibility. However, manpower requirements are heterogeneous among flights. The actual manpower required by a team must satisfy the maximum requirements among all flights in the team pairing, which leads to substantial manpower waste. On the contrary, in MICCPP-ACCS, facilitated by the individual scheduling approach and CCS, cabin crews can be scheduled with much higher flexibility. In the tested instances under all availability levels, it is found that no cabin crew is wasted on any flight by MICCPP-ACCS (see the 4th column of **Table 12**). Besides, the solutions of MICCPP-ACCS for HX/RE-60% and HX/RE-50% instances are the same, implying that the 60%/50% availability level is very sufficient for MICCPP-ACCS, so that the proposed model can identify the elapsed-time-minimization solutions without the concern of manpower limitation. In other words, for HX/RE-60%/50% instances, the manpower availability constraint can be relaxed in MICCPP-ACCS, while no manpower waste occurs. In comparison, extensive manpower idle time exists through the TCCPP approaches for HX/RE-60%/50% instances. We thus conclude that even without manpower availability restrictions, the proposed MICCPP-ACCS still performs better than the traditional models through increased manpower utilization.

Extra manpower requirement & Controlled crew substitution. In HX/RE-60% instances, manpower availability is sufficient for all models (i.e., TCCPP-TAFB, TCCPP-Availability and MICCPP-ACCS). For HX/RE-50% and HX/RE-40% instances, MICCPP-ACCS can operate all flights using the available manpower, while both TCCPP-TAFB and TCCPP-Availability should hire extra manpower. TCCPP-Availability shows much lower dependence on extra manpower than TCCPP-TAFB. For instance, in H1-40%, TCCPP-TAFB requires 237 extra crews, while only 15 are needed for TCCPP-Availability. Therefore, the significance of considering manpower availability in cabin crew pairing is highlighted. For HX/RE-30% instances, even for MICCPP-ACCS, the available manpower is in a shortage. For TCCPP-TAFB and TCCPP-Availability, more extra cabin crews are needed under the 30% availability level compared to the HX/RE-50% and HX/RE-40% cases. In contrast, for MICCPP-ACCS, the function of CCS can help deal with the manpower-insufficiency dilemma, which eliminates the demand for extra manpower. For example, in H5-30%, MICCPP-ACCS applies 287 substitutions, while TCCPP-TAFB and TCCPP-Availability employ 5765 and 1980 extra crews, respectively. Thus, the merit of CCS in reducing the impact of manpower shortage on cabin crew scheduling is demonstrated.

Elapsed time (operating cost). For TCCPP-TAFB and TCCPP-Availability, under the most-sufficient cases (HX/RE-60%), the total TAFB pairing costs (i.e., total elapsed time) are identical, which are higher than that of MICCPP-ACCS. When the availability level decreases, TCCPP-Availability tries to fulfill flights' manpower requirements using the available manpower as much as possible with the minimum employment of extra manpower. Therefore, TCCPP-Availability generates longer pairings with higher TAFB pairing costs along with the decline in available manpower. Accordingly, the total TAFB pairing cost of TCCPP-Availability is 5.6% higher than that of TCCPP-TAFB on average. The average cost reduction (i.e. elapsed time reduction) achieved by MICCPP-ACCS is 8.4% compared to TCCPP-TAFB, and 13.2% compared to TCCPP-Availability. Under the most-insufficient cases (HX/RE-30%), MICCPP-ACCS has to derive long pairings and apply CCS to cover all flights' requirements. Therefore, in H1-30% and H2-30% instances, the total TAFB pairing cost of MICCPP-ACCS is slightly higher than that of TCCPP-TAFB, but still lower than that of TCCPP-Availability. This shows that MICCPP-ACCS improves manpower utilization when encountering manpower shortage problems at the cost of elapsed time, to avoid manpower waste and extra manpower employment. However, in H3-30%, H4-30%, H5-30%, and RE-30% instances, MICCPP-ACCS is still more cost-efficient than TCCPP models.

Through the above analyses, compared to TCCPP, it is concluded that the proposed MICCPP-ACCS can significantly reduce manpower waste (thus improving cabin crew utilization) and operating costs through the increased flexibility of cabin crews facilitated by the individual scheduling approach and controlled crew substitution. In the tested large instances (both real and hypothetical), MICCPP-ACCS can even eliminate idle crews. When the available manpower is insufficient, MICCPP-ACCS is able to reduce extra manpower demand by sacrificing elapsed times. Besides, it is shown that even without the manpower availability constraint, MICCPP-ACCS still performs better than the traditional models.

<u>6.2.2 Performance of the Proposed Genetic Algorithm</u>

In this section, we examine the performances of the newly proposed Genetic Algorithm. It is realized that the solutions obtained by metaheuristics are usually different in every run due to the randomness existing in the algorithms, e.g., formation of solution pool, crossover, and mutation in GA. The solution deviation may become larger when the problem gets more complicated. In metaheuristic studies, it is well recognized that if the solution deviation is below 5%, the developed algorithm can be regarded as stable and is acceptable. In our study, for each instance under each tested manpower availability level (i.e., 60%, 50%, 40%, and 30%), the Genetic Algorithm runs for 50 times to test the stability of solutions. The average solution deviation is summarized in **Table 13**. It is seen that for all simple cases (i.e., HX/RE-60%/50% cases in which the available manpower is sufficient), the solution deviation is zero. The deviation grows when the problem becomes more complicated (i.e., HX/RE-40%/30% cases in which the available manpower becomes insufficient). However, even for the largest instance and the most complicated cases, the average solution deviations are below 3%. Therefore, our proposed Genetic Algorithm is shown to be stable and acceptable.

Table 13. Solution deviation for 50 runs of the proposed Genetic Algorithm.

Instance	Manpower availability	Average deviation	Instance	Manpower availability	Average deviation
H1	60%	0.00%	H4	60%	0.00%
	50%	0.00%		50%	0.00%
	40%	0.80%		40%	1.94%
	30%	0.80%		30%	1.99%
H2	60%	0.00%	H5	60%	0.00%
	50%	0.00%		50%	0.00%
	40%	1.31%		40%	2.62%
	30%	1.35%		30%	2.78%
H3	60%	0.00%	RE	60%	0.00%
	50%	0.00%		50%	0.00%
	40%	1.58%		40%	2.73%
	30%	1.53%		30%	2.78%

Besides, we examine the optimality gaps between the solutions obtained by (i) the proposed Genetic Algorithm and (ii) Column Generation + Mixed Integer Programming (CG+MIP), with the LP lower bounds provided by the column generation method. As the proposed MICCPP-ACCS schedules each cabin crew class (both available and extra ones) individually, the problem scale and complexity are very high. To obtain LP lower bounds and MIP solutions within reasonable computational times, we utilize 18 relatively small-scale instances to examine the optimality gaps, which are demonstrated in **Table 14**. It is shown that the average optimality gap obtained by CG+MIP is 0.0076%, and two cases (i.e., 141-L3 and 152-L3) even achieve zero gap. For the proposed Genetic Algorithm, it is reasonable to observe higher optimality gaps. However, the average optimality gap is only 0.1730%, while the highest gap (the case of 242-L3) is 0.2767%, which is acceptable and shows the good performances of the proposed Genetic Algorithm. Regarding computational times, all these instances can reach steady stage within 2 seconds by using the proposed Genetic Algorithm. However, for column generation and MIP, much longer times (e.g., thousands of second) are required, especially when the instance scale grows larger. Therefore, the proposed Genetic Algorithm is shown to be able to provide satisfactory outcomes in a quick manner.

Table 14. Optimality gap.

No. of flights*	LP lower bound obtained by column generation	CG+MIP solution	CG+MIP gap	Proposed GA solution	Proposed GA gap
77-L1	651,113,381.67	651,178,685	0.0100%	651,283,547	0.0261%
81-L1	1,801,015,758.33	1,801,172,135	0.0087%	1,802,355,562	0.0744%
83-L1	1,850,948,162.50	1,850,971,340	0.0013%	1,852,245,683	0.0701%
84-L1	151,218,525.00	151,232,655	0.0093%	151,318,657	0.0662%
85-L1	351,053,601.39	351,064,955	0.0032%	351,251,778	0.0565%
92-L1	2,301,032,143.33	2,301,040,190	0.0003%	2,302,582,454	0.0674%
141-L2	16,740,166.25	16,742,270	0.0126%	16,774,359	0.2043%

152-L2	16,738,930.00	16,740,710	0.0106%	16,770,867	0.1908%
188-L2	747,393,190.62	747,434,715	0.0056%	748,895,733	0.2010%
201-L2	707,546,378.33	707,580,535	0.0048%	709,386,368	0.2601%
242-L2	1,453,040,393.54	1,453,184,845	0.0099%	1,456,698,793	0.2518%
252-L2	1,368,332,762.50	1,368,360,345	0.0020%	1,371,968,754	0.2657%
141-L3	1,316,670.00	1,316,670	0.0000%	1,319,465	0.2123%
152-L3	1,331,990.00	1,331,990	0.0000%	1,334,758	0.2078%
188-L3	2,038,753.33	2,038,945	0.0094%	2,043,324	0.2242%
201-L3	2,110,017.50	2,110,085	0.0032%	2,114,543	0.2145%
242-L3	2,739,176.00	2,740,020	0.0308%	2,746,754	0.2767%
252-L3	2,777,760.00	2,778,190	0.0155%	2,784,538	0.2440%
		Average	0.0076%	Average	**0.1730%**

*L1 refers to manpower availability (29, 35, 54, 63), L2 refers to manpower availability (51, 65, 94, 109), while L3 refers to manpower availability (151, 165, 194, 209).

7. Concluding Remarks

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 heterogeneous flight requirements of various aircraft types (families), which leads to low manpower utilization and high operating costs. Based on the research gaps and the observed real-world airline operations, this work 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. Besides, a simplified version without the function of CCS, named MICCPP-A, is developed to derive managerial insights. A column generation based heuristic approach (CG+MIP) is derived to obtain the solutions. 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.

To examine the distinctive features of MICCPP-ACCS, we conduct computational experiments based on small-scale instances that are derived from real-world collected flight schedules of a Hong Kong based airline. Specifically, we analyze the flight manpower requirement benchmarks for each instance, and investigate the characteristics of the diverse manpower availability-requirement scenarios. Besides, we demonstrate the crucial effect of CCS on cabin crew scheduling in dealing with the manpower shortage dilemma. In addition, we apply a series of large hypothetical instances to validate and confirm the superior performances of MICCPP-ACCS over TCCPP. By comparing with two types of TCCPP (TCCPP-TAFB and TCCPP-Availability), we demonstrate that MICCPP-ACCS can significantly reduce manpower waste, and shows great potential in operating cost reduction. Even without manpower availability constraints, MICCPP-ACCS can achieve better performances than the traditional team-based models. Therefore, by modelling cabin crews individually and considering the strategy of CCS, our proposed MICCPP-ACCS is practically useful and efficient.

However, as our main focus is enhancing cabin crew pairing decisions from the perspective of airlines (i.e., improving manpower utilization), we apply the "time away from base (TAFB)" to approximate the costs of a pairing. In reality, pairing costs involve complex and non-linear cost components, including pairing elapse time, duty work time, minimum guaranteed paid time, deadhead costs, short sit penalties, short rest penalties, etc. Therefore, merely applying TAFB as the pairing cost may lead to solution bias, which constitutes a major limitation for this study. Therefore, a promising future research direction is to consider the impact of other cost functions on the individual scheduling approach. Besides, the "manpower availability constraint" considered in MICCPP-ACCS refers to the maximum number of pairings that can be generated for a week, which is a rough approximation of the actual manpower demand. Applying this constraint may not perform well (e.g., generate very long pairings), also leading to solution bias. More precise manpower availability constraints could be considered in future research, like base flying time restrictions and the maximum number of pairings per day.

Moreover, starting from late 2019, the COVID-19 epidemic has totally re-shaped the airline industry. The crew members operating international flights have to go through a long period (e.g., 14 days) of quarantine after duties in many countries (e.g., in China). Even for the manpower operating domestic flights, they are under heathy risks as new positive cases arise from time to time. The planned crew schedules are easily disrupted if some positive cases or close-contact persons appear on the flight (as the crew members would be unavailable in the following days). Thus, the epidemic has created a great manpower-uncertainty challenge for airlines. Therefore, the new crew scheduling approach and the crew substitution strategy studied in this paper becomes more important from this aspect.

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