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Airline crew scheduling: Models and algorithms

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ABSTRACT

The airline crew scheduling problem has become a crucial but challenging task for commercial airlines for decades. Airlines are operating with two types of air crew: cockpit crew and cabin crew. Due to the unique operating characteristics, the scheduling problems for these two crew types are very different. Besides, according to the planning stage, the airline crew scheduling problem can be classified as tactical planning problems (traditional scheduling and robust scheduling, weeks or months before the actual operations) and operational planning problems (recovery, after disruptions have occurred during the operational stage). Realizing the significance of the airline crew scheduling problems and a lack of review on the modelling and algorithmic advancements in terms of each crew type and planning stage, we develop this paper to review the related literature from four aspects: the scheduling for cabin crew, the scheduling for both cabin crew and cockpit crew, the robust scheduling for cockpit crew, and the recovery for cockpit crew. For each stream, we examine a number of prior representative studies to review the advancements in model development and solution algorithm construction to generate insights. Finally, we conclude the review by proposing a future research agenda for the airline crew scheduling problem.

1. Introduction

1.1. Background

The air transportation industry has become a crucial part for both the passenger transportation (Atkinson et al., 2016; Cui et al., 2019; Hu et al., 2013; Wang & Jacquillat, 2020) and the cargo delivery all over the world (Chung et al., 2020; Wen et al., 2019). Due to the intensive market competition (Lijesen & Behrens, 2017; Scotti & Volta, 2017), airlines are struggling to improve their decision making in various aspects, such as pricing strategies (Ma et al., 2020), financial hedging tactics (Merkert & Swidan, 2019), and behavioral analysis (Kang & Hansen, 2017; Nicolae et al., 2017; Sheng et al., 2019). In terms of operational decisions, the airline scheduling problem is especially critical to properly manage the diverse resources (e.g., aircraft, crew, seat inventory) with the assistance of operations research techniques (Bish et al., 2011; Etschmaier & Mathaisel, 1985; Jiang & Barnhart, 2009).

The airline scheduling problem is further categorized into the *tactical planning problem* (carried out weeks or even months before the operation date) and the *operational planning problem* (conducted during the operational stage for recoveries after disruptions occur)

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according to the time of the decision making (Tekiner et al., 2009; Wang & Jacquillat, 2020; Wen et al., 2020b), as depicted in Fig. 1. Generally speaking, cost-minimization scheduling is the focus of the tactical planning stage. However, in recent years, due to the highly volatile operating environment, airlines are moving from the traditional cost-minimization scheduling to the *robust scheduling*, with the aim of enhancing the solution robustness to better hedge against the potential disruptions in real operations. On the other hand, in the operational stage, *recovery* is used to bring the disrupted operations back to schedule in order to alleviate the negative impacts of various disruptions that have happened (Aktürk et al., 2014; Chung et al., 2015, 2017). *Disruption management* for aircrew (involving both the robust scheduling and recovery) has attracted increasing attention due to the highly volatile and uncertain operating environment in the aviation industry. Generally, the robust scheduling problems and recovery problems are more complicated in various aspects (like the modelling approach, decision variables) than the traditional cost-minimization based scheduling problems as robustness measures or recovery strategies shall be considered. Besides, decision makers should also evaluate the tradeoffs between the operating costs and robustness enhancement (or recoveries).

Considering the large problem scale and high complexity, the airline scheduling problem is generally solved by sequentially dealing with a flight scheduling problem, fleet assignment problem, aircraft maintenance routing problem, and a crew scheduling problem (Cadarso et al., 2017). First, *flight scheduling* decides the flight routes to serve and the corresponding flight frequency. Second, *fleet assignment* assigns an aircraft type (i.e., fleet) to each flight scheduled. Then, the routes for each individual aircraft in a fleet are planned according to the maintenance requirements in *aircraft maintenance routing*. Lastly, as the final stage of airline scheduling, *crew scheduling* is crucial for airlines' operations efficiency and overall performances by assigning crew members to serve the scheduled flights with the aim of cost minimization. Fig. 2 demonstrates the sequential stages in the airline scheduling.

Among these airline scheduling problems, the crew scheduling problem has attracted extensive attention from both the academia and the industry, which is motivated by the problem's practical significances and industrial challenges. First of all, the crew-related cost (e.g., payments) has become the second largest component of the total operating costs of an airline, just after the fuel expenditure (Barnhart et al., 2003; Sibdari et al., 2018). Even a slight improvement in crew scheduling solutions may lead to a million-dollar cost saving. Besides, the research of airline crew scheduling provides an opportunity to investigate many of the components common to other crew scheduling problems, while the airline planning involves more efforts and uncertainties. However, due to the vast number of rigorous working rules and regulations imposed by diverse authorities such as labor unions, governments, and airlines (Button et al., 2019), the millions or even billions of possible crew schedules, as well as enormous variables (most of which are integers) generated in the solution process, the airline crew scheduling problem is still unmanageable. Moreover, the unpredictable disruptions bring great challenges to the optimization of airline scheduling, which call for robust or recoverable schedules. Besides the general disruptions like the extreme weather or propagated delay, the current global epidemic situation can be regarded as a huge disruption to the entire global aviation transportation system, which propose broad impacts and further requirements on domestic or international flights scheduling as well as the qualifications and arrangement of crews, and therefore, further refinements or even new models or approaches are demanded.

The airline crew scheduling is commonly decomposed into a crew pairing problem and a crew assignment/rostering problem to make it tractable (Barnhart & Cohn, 2004). The *crew pairing problem* is to generate sufficient anonymous feasible pairings to satisfy all flight's manpower requirements while minimizing the total operating costs. A feasible *pairing* is a sequence of flights to be served by the same crew member which starts from and ends at the crew member's home base. Then, in the *crew assignment/rostering problem*, the pairings constructed in the crew pairing problem are connected to form monthly assignments/rosters to be assigned to specific crew members (Zeighami & Soumis, 2019). More specifically, the assignment/rosters problem determines the individual crew schedules to cover a set of crew pairings. It should be guaranteed that each pairing is served by the needed number of crews so that the flights could be fully staffed. To optimize the experience of both the crews and the customers, the crew assignment should also consider crew specialties and demands, such as crew qualifications, rest status and crew preferences. In the literature, the crew pairing problem is studied more than the crew assignment/rostering problem, as the former problem is the first stage of the airline crew scheduling problem which is especially critical for the overall quality of the final crew schedules. Therefore, in this study, we mainly focus on reviewing the advancements in the crew pairing problem.

The airline crew pairing problem can be divided into single-base problems and multi-base problems according to the number of home bases considered (Wang & Wang, 2019b). This classification depends on the scale and deployment of airlines. Smaller airlines like those operated by cities might have only one base where to perform operating activities such as scheduling and maintenance.

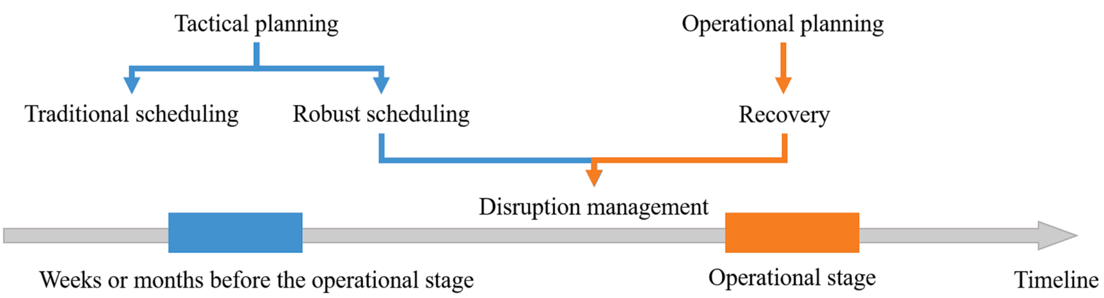

Fig. 1. The categories of the airline scheduling problems.

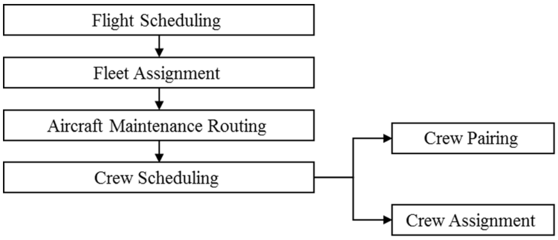

Fig. 2. The stages of airline scheduling.

While airlines that serve a large geographical area often establish multiple bases distributed in different regions to broaden spatial coverage and improve operating efficiency (Wang & Wang, 2019b). Note that the crew pairings generated for both the single-base and multi-base problems share the same character that a crew pairing should start and end at the same base. Besides, two categories of flight networks are used in the literature for pairing generation (Tu et al., 2020; Wang & Wang, 2019a; Wong et al., 2020; Wu & Law, 2019). They are flight-based networks and duty-based networks. The latter type is commonly applied because the optimization efficiency is enhanced by considering some of the regulations during network construction (Vance et al., 1997). In other words, as the detailed regulations or rules between flights have been satisfied and encapsulated in duties, the optimization efficiency of the duty-based network could be greatly improved since only the relationships between duties rather than between individual flights should be managed. A typical duty-based flight network is demonstrated in Fig. 3. A *duty* is composed of a sequence of flights separated by *transits* (or *sits*), 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 crew members are free from any duty. A legal pairing can then be regarded as a sequence of duties connected by rests, operated by the same crew, which starts/ends at the home base, and satisfies diverse working rules and regulations such as the maximum elapse time and maximum number of flights allowed in a pairing. The total elapse time of a pairing is known as the *time away from base* (TAFB) in the literature. In some cases, crew members are placed on a scheduled flight as passengers for repositioning to an airport where they are required to operate duties. This type of flights is called as *deadhead*. A typical pairing generally lasts for two to five days, while a crew member commonly flies four to five pairings in a month.

Regarding the solution methodology, date back to 1970s, Marsten et al. (1979) reported a successful application of the integer programming approach for the crew planning problem. From then on, the airline crew pairing problem is generally modelled as a set-covering problem or a set-partitioning problem. As the number of possible pairings is enormous, researchers traditionally adopted a "once for all generation technique". In this technique, a sufficiently large number of "good" pairings are generated by using heuristics. Then, a set-covering or set-partitioning problem is applied to identify a sub-set of pairings with a minimum cost through using integer programming techniques like branch-and-bound, cutting planes, and sub-gradient optimization. However, due to the high problem complexity, many studies solve the problem heuristically (Azadeh et al., 2013; Cohn and Barnhart, 2003; Levine, 1996). For example, to deal with the airline crew scheduling, Azadeh et al. (2013) developed a hybrid particle swarm optimization (PSO) algorithm synchronized with a local search heuristic and compared the performance of the hybrid PSO algorithm with other heuristic algorithms developed based on genetic algorithm and ant colony optimization. However, the quality of solutions generated by heuristic approaches cannot be guaranteed. Levine (1996) proposed a hybrid genetic algorithm that combines the genetic algorithm with a local search heuristic for airline scheduling, while experiments demonstrated that results obtained by optimization approaches (i.e., branch-and-cut and branch-and-bound) outperformed the hybrid algorithm. Moreover, Cohn and Barnhart (2003) formulated the integrated problem of crew pairing and aircraft maintenance routing with an extended model and solved the model both heuristically and optimally, which explored the trade-off between the calculation time and the result quality. Later in 1980s, Lavoie et al. (1988) made a

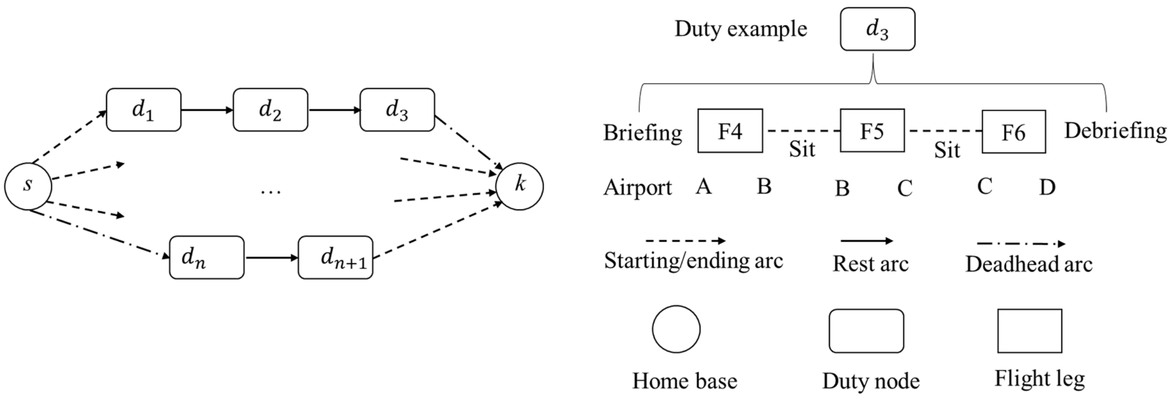

Fig. 3. A typical duty-based flight network.

remarkable progress in the solution approach for the crew pairing problem by proposing a column generation based technique to deal with this large-scale problem. The column generation (CG) technique is a continuous optimization technique to deal with large-scale linear programming problems. To be specific, the CG can implicitly consider all variables without the challenge of explicitly dealing with all variables (Desaulniers et al., 2005). Accordingly, in the CG, the whole optimization problem is divided into a restricted master problem with a limited number of pairings and a sub-problem that is used to generate new potential pairings. To obtain integer solutions, the branch-and-price methodology is often applied (Barnhart et al., 1998; Luo et al., 2016).

1.2. Contribution and paper structure

In recent years, a large body of research has been devoted to the airline crew scheduling problem due to the significance of air crew for airlines' profitability and survival in the current highly volatile and competitive market conditions. In the literature, there are a number of review studies on the problem. For example, Barnhart et al. (2003) and Gopalakrishnan and Johnson (2005) provide tutorial-based reviews for the problem. Deveci and Demirel (2018) provide a survey on the general problem settings and the operations research (OR) techniques for the modelling and solution methodologies. Moreover, some studies review the advances for more than one stage of the airline scheduling problems, like Eltoukhy et al. (2017) which review the works related to flight scheduling, fleet assignment, aircraft maintenance routing, and crew scheduling, and Parmentier and Meunier (2020) which focus on aircraft maintenance routing and crew scheduling. Besides, concentrating on the airline disruption management, Clausen et al. (2010) review the model features of the recovery studies for aircraft, crew, and passenger, while Chung et al. (2015) provide a comprehensive overview from both the recovery and robustness perspectives.

In this paper, we aim to review some selected important and representative research studies on the airline crew scheduling problem. In terms of the structure of the review, we organize the selected research papers according to the type of crew studied and the planning stage of the problem considered. The logic and contribution of this taxonomy are explained as follows. Airlines are operating with two distinct types of air crew. They are cockpit crew and cabin crew. These two crew types are very different in operating characteristics, which greatly affects the scheduling (pairing) problems for them, including the modelling approaches, the format of decision variables, and the structure of constraints. As will be discussed later in Section 2, the problem scale and complexity of the cabin crew pairing problem are much higher than those of the cockpit crew pairing problem due to the various distinctive operating characteristics of cabin crew (e.g., multiple classes, mixed-qualification, heterogeneous manpower requirements, crew substitution). Therefore, the existing scheduling studies on cabin crew are mainly traditional cost-minimization pairing problems without disruption considerations. On the other hand, due to the relatively simpler operating features, studies on cockpit crew can be extended to consider robustness or recovery operations in addition to cost minimization. Therefore, in this paper, we review the advancements of the selected studies based on the crew types and planning stages investigated. To the best of our knowledge, our study is the first paper in the literature which examines the modelling and methodological advancements in the scheduling problem for each type of air crew and in the different planning stages. By applying this review structure, we are able to obtain a profound understanding regarding the state-of-the-art status of the domain in terms of the significant advances in model development and solution algorithm construction for each crew type and planning stage, which provides a solid foundation for us to propose a future research agenda. To be specific, the reviewed literature is classified into four categories as demonstrated in Fig. 4: the scheduling for cabin crew, the scheduling for both types of crew (cabin/cockpit crew), the robust scheduling for cockpit crew, and the recovery for cockpit crew. Based on the critical review for each category, we then propose promising future research directions.

The remaining of this paper is structured as follows. Section 2 discusses the differences between the scheduling problems for cockpit crew and cabin crew. Section 3 reviews the selected representative scheduling studies for cabin crew. Next, the research on both cockpit crew and cabin crew is discussed in Section 4, which is followed by the robust scheduling studies on cockpit crew in Section 5. Section 6 then examines several studies for cockpit crew recovery. Last, Section 7 recommends a future research agenda, while Section 8 concludes for this work.

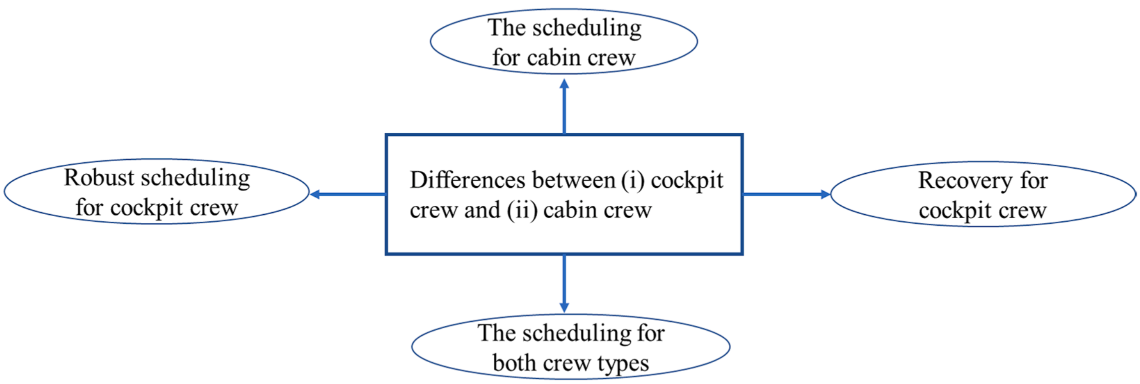

Fig. 4. Core elements under investigation.

2. Differences between the scheduling for cockpit crew and cabin crew

The scheduling problems for cockpit and cabin crew are different in various aspects as discussed below. First of all, we summarize the operating characteristics of cockpit crew and cabin crew in Table 1.

Cockpit crew members are essential for the operations of an aircraft. Therefore, the training for cockpit crew is long-term and capital-intensive. Generally speaking, cockpit crew is single-qualified to operate one type of aircraft (family) with license. Accordingly, the scheduling problem for cockpit crew is decomposed according to the type of aircraft, so that the problem scale can be reduced. Although cockpit crew is classified into various classes (such as captain, first officer, and second officer) according to their experiences and skills, they are modelled as teams (i.e., the team modelling approach) due to the fact that the manpower requirements of flights operated by the same aircraft type is homogeneous as regulated by the aircraft operating manual (Shebalov & Klabjan, 2006). Accordingly, the flight coverage requirement is simplified to ensure that each flight is covered by (at least) one team. The general form of the mathematical model for the team-modelling crew pairing problem is shown in Eq. (1) to Eq. (3). The binary decision variable x_p represents whether to select Pairing p from the whole pairing pool (denoted by P), while each pairing is for a cockpit crew team. The cost of Pairing p is indexed by c_p. The objective function Eq. (1) is to minimize the total operating costs for all the pairings selected, while Constraint Eq. (2) ensures that each flight ($\forall f \in F$) is covered (at least) once (i.e., each flight is covered by (at least) one cockpit crew team). Therefore, Eq. (2) is also named as the *flight coverage constraint* in the literature. The flight coverage coefficient a_{pf} is equal to 1 if Pairing p covers Flight f. Otherwise, a_{pf} takes the value of zero. In Eq. (2), if the "equal to or larger than" sign is used, it is a set-covering problem. Instead, if the "equal to" sign is applied, it is a set-partitioning problem.

$$\text{Min} \quad \sum_{p \in P} c_p x_p \tag{1}$$

$$\text{s.t.} \quad \sum_{p \in P} a_{pf} x_p \geq (=) 1, \forall f \in F \tag{2}$$

$$x_p = 0 \quad \text{or} \quad 1, \forall p \in P \tag{3}$$

Cabin crew members are responsible for the safety of passengers in the aircraft cabin, and they are mixed-qualified to serve several types of aircraft with proper training (ICAO, 2010). Similar to cockpit crew, cabin crew members are also categorized into various classes such as pursers, flight attendants, stewards, and cabin mates. Different from cockpit crew, due to the cross-qualification, the scheduling problem for cabin crew is not able to be decomposed by aircraft types with the aim of reducing problem scale. Besides, the manpower requirements for each class of cabin crew on different types of aircraft are distinct. For example, in addition to the minimum requirements to guarantee passengers' safety as required by authorities (e.g., at least one cabin crew member for each pair of doors of the aircraft), airlines commonly provide high service levels by assigning more cabin crew members to flights. Actually, even for the same aircraft type, different cabin layouts would lead to different cabin crew requirements. Accordingly, the flight coverage constraint of the pairing problem for cabin crew is different from that for cockpit crew (i.e., Eq. (2)). To be specific, it is critical to ensure that the heterogeneous manpower requirement for each class of cabin crew of each flight is satisfied. If we use $r \in R$ to represent the cabin crew classes, and apply b_f^r to denote the number of Class r cabin crew members required by Flight f, then, the flight coverage constraint for the cabin crew pairing problem can be formulated as Eq. (4). Note that the subscript r for Pairing p_r is utilized to represent the pairings for Class r cabin crew.

$$\sum_{p_r \in P_r} a_{p_r f} x_{p_r} \geq b_f^r, \forall f \in F, \forall r \in R \tag{4}$$

Based on the above discussion, it is undoubtable that characterizing distinctive operating features of cabin crews is critical in crew scheduling problems. More specific summarize of consequences resulted by neglecting such features is provided in Table 2.

In conclusion, the problem scale and complexity of the cabin crew scheduling problem are much higher than those for cockpit crew. Besides, due to the relatively higher payment for cockpit crew than cabin crew, the scheduling problem for cockpit crew has gained much more attention in both the literature and the industry. However, the scheduling decisions for cabin crew are also critical for an airline as they occupy a major component of airline manpower. Therefore, the overall cabin crew related costs are significant. Besides, they are important to ensure the comfort and satisfaction of passengers, as well as provide emergency and evacuation functions to guarantee passengers' safety, which is essential for the image development of an airline. Therefore, enhancing the decision making for cabin crew scheduling is also of great importance.

Table 1
Operating characteristics for two types of aircrew.

Characteristics	Cockpit crew	Cabin crew
Aircraft qualification	Single-qualified	Cross-qualified
Manpower requirement	Homogeneous within an aircraft type	Heterogeneous across aircraft types and cabin layouts
Crew substitution	NA	Existing in some airlines

Table 2
Consequences of failing to consider the cabin crew features.

Consequences	Explanations
Impairing Operating Efficiency	Different from the cockpit crews who are restricted in the fleet type that they can fly, a cabin crew can serve mixed types of aircrafts. Scheduling the cabin crews in the same way as the cockpit crews will miss this diversity. As flights are facing with heterogeneous manpower requirement for each class of cabin crew, the team modelling approach for cockpit crew is no longer applicable for cabin crew. Otherwise, manpower resource waste as well as high operating costs will be incurred as the actual manpower required by a team must satisfy the maximum requirements among all flights in the team pairing (Wen et al., 2020a).
Problematic Schedules	Different aircrafts have distinct requirements in terms of the number or the qualifications of the cabin crews. Ignoring the distinct characteristics of the cabin crews can lead to problematic schedules.
Unexplored Recovery Strategies	The special features of the cabin crews can facilitate the development of different operations recovery strategies for cabin crews when facing a disruption, such as the crew substitution (i.e., assign cabin crew members to substitute the ones from other classes in a shortage). The operations manager may lose chances to obtain efficient recovery plans without the considerations of cabin crew characteristics.

3. Scheduling for cabin crew

In the literature, there are only a few studies that concentrate on improving the decision making for cabin crew pairings which are reviewed in this section. The problem and model features of these studies are listed in Table 3 and Table 4, respectively.

In the literature, the crew pairing problem is generally formulated as a set-partitioning problem or a set-covering problem (as shown in Section 2). Differently, Yan and Tu (2002) develop a pure network model to solve a cabin crew pairing problem for a small-scale Taiwan-based airline as shown from Eq. (5) to Eq. (9), which is distinct from the commonly used approaches. In the pure network model of Yan and Tu (2002), the decision variables ($x_{ij}, (i,j) \in A$) are for each arc in the flight network ($G = (N,A)$), instead of for each potential pairing. Therefore, the flight coverage constraint Eq. (2) is modified into network flow balance restrictions and arc coverage constraints. To be specific, Eq. (6) is the flow conservation constraint, while Eq. (7) ensures that each scheduled flight or work duty (contained in the arc set L) is to be served by a crew. Besides, Eq. (8) and Eq. (9) restrict that all decision variables are non-negative integers. Different from the common flight networks in which a source-sink path is not necessarily a feasible pairing (as some pairing-related working rules and regulations might be violated), the network constructed by Yan and Tu (2002) can ensure that every source-sink path is a legal pairing as all working rules and regulations are considered and satisfied during network construction. Therefore, the optimization objective of Yan and Tu (2002) is to identify a sub-set of pairings from all the source-sink paths contained in the constructed network in order to cover all flights with a minimum cost. Accordingly, a minimum-cost pure network flow model is formulated in Yan and Tu (2002), which is solved by the network simplex method. Yan and Tu (2002) insist that their proposed pure network modelling approach is advantageous than the traditional set-covering/set partitioning models which are generally solved by column generation as the solutions obtained are completely integers. However, for large-scale problems, the construction of a pure network which can ensure that all source-sink paths are feasible pairings is an extremely challenging task.

$$\text{Min} \quad \sum_{(i,j)\in A} c_{ij}x_{ij} \tag{5}$$

$$\text{s.t.} \quad \sum_{j\in O(i)} x_{ij} - \sum_{k\in I(i)} x_{ki} = 0, \forall i \in N \tag{6}$$

$$x_{ij} = 1, \forall (i,j) \in L \tag{7}$$

$$x_{ij} \geq 0, \forall (i,j) \in A \backslash L \tag{8}$$

$$x_{ij} \quad \text{are non}-\text{negative integers}, \forall (i,j) \in A \tag{9}$$

Recently, Quesnel et al. (2020a) integrate the language requirements for cabin crew members into the decision framework of the crew pairing problem. Traditionally, the language constraints are considered in the crew assignment stage, which implies that the pairings generated in the crew pairing stage might not be compatible with the skills of the available cabin crew members. In order to reduce the language-violated pairings produced in the crew pairing problem, Quesnel et al. (2020a) thus propose a new crew pairing problem variant with language constraints (named as the CPPLC) in which two types of soft language restrictions (i.e., monthly and daily constraints) are considered. The specific manpower requirement for cabin crew members for each flight leg is considered in the crew assignment/rostering problem proposed by Quesnel et al. (2020a). However, the multiple classes of cabin crew are not specified, and the pairings generated in the crew pairing problem are still in a team format. In the crew pairing model developed by Quesnel et al. (2020a), in addition to the flight coverage constraint and the language constraint, the base working time limitation is also considered, to ensure that the base constraint can be satisfied. A branch-and-price heuristic solution algorithm is developed. Real-world validation shows that the solutions produced by the proposed CPPLC are more suitable for the crew assignment/rostering stage, leading to a significant reduction in the number of language-violated constraints (Quesnel et al., 2020a).

Different from the literature discussed above, Yan et al. (2002) and Wen et al. (2020a) construct pairings for individual cabin crew members. Wen et al. (2020a) point out that failing to consider the distinctive operating characteristics of cabin crew (i.e., multiple

Table 3
Problem features for the literature reviewed in Section 3.

Literature	Home base		Modelling approach		Manpower requirement		Crew substitution	
	Multi-base	Single-base	Team	Individual	Homogeneous	Heterogeneous	Controlled	Not-controlled
Yan and Tu (2002)		√	√		√			
Yan et al. (2002)	√			√		√		√
Wen et al. (2020a)		√		√		√	√	
Quesnel et al. (2020a)	√		√		√			

Table 4
Model features for the literature reviewed in Section 3.

Literature	Model format	Objective		Flight coverage constraint		Solution approach	
		Cost minimization	Others	Each flight is covered by (at least) once	Specific requirements are considered	Column generation based	Others
Yan and Tu (2002)	Network flow problem	√		√			Network simplex method
Yan et al. (2002)	Set-covering problem	√			√	√	
Wen et al. (2020a)	Set-covering problem	√	Substitution penalty, extra manpower penalty		√	√	Genetic algorithm
Quesnel et al. (2020a)	Set-partitioning problem	√	Constraint penalties	√		√	Branch-and-price heuristic

classes, cross-qualification, heterogeneous manpower requirements) during pairing generation will lead to a high expenditure related to pairing re-construction during the crew assignment stage for solution feasibility. Besides, through comparing the solutions obtained from the traditional team-modelling approach with those from the individual-modelling approach, Wen et al. (2020a) demonstrate that modelling the multi-class cabin crew in the team basis can lead to lower manpower utilization and high operating costs. The heterogeneous manpower requirements for each class of cabin crew for each flight are considered in both Yan et al. (2002) and Wen et al. (2020a). Therefore, the flight coverage constraint in these two studies are more than just to ensure that each flight is covered (at least) once. Besides, these two studies formulate the real airline operation, i.e., crew substitution (i.e., to assign a cabin crew member from other classes to substitute the originally required one). However, they are different in the following aspects. First, Wen et al. (2020a) consider the manpower availability constraint in the stage of crew pairing problem. The crew substitution in Wen et al. (2020a) is utilized to deal with the problem of manpower shortage. A penalty cost will be incurred in the objective function along with a substitution to avoid the abuse of crew substitution. We use Fig. 5 to demonstrate the mechanism of the so-called controlled crew substitution proposed in Wen et al. (2020a). In this example, Flight 10 demands two Class 1 cabin crew members and only one for Class 2. However, there is only one available crew member for Class 1, leading to a manpower shortage for this cabin class on Flight 10. Fortunately, there is an extra Class 2 cabin crew member who operates a deadhead duty on Flight 10 for positioning purposes, who can be assigned to serve as a "temporary" Class 1 crew to ensure the normal operations of this flight. Accordingly, the strategy of controlled crew substitution can help alleviate the dilemma of manpower shortage in Wen et al. (2020a). On the other hand, the crew substitution developed by Yan et al. (2002) is mainly for cost minimization. Second, in the crew substitution scheme of Wen et al. (2020a), at least one cabin crew member from the originally required class will be assigned to each flight, to ensure a certain service level, while this is not guaranteed in Yan et al. (2002). It is possible that for a certain cabin crew class on a certain flight, all crew members assigned are from other classes in Yan et al. (2002). Third, extra manpower is introduced in Wen et al. (2020a) to ensure solution feasibility, in case that the flight manpower requirements can't be fully satisfied even with the assistance of crew substitution, which is not considered in Yan et al. (2002). As a result, the crew substitution constructed in Wen et al. (2020a) is controlled for the purpose of solving the dilemma of manpower shortage, instead of merely for cost minimization. As for the solution approach, both studies apply a column-generation based methodology. However, as multiple cabin crew classes and extra manpower are considered, the problem scale of Wen et al. (2020a) is very high in terms of the number of constraints and number of variables. Accordingly, a genetic algorithm is also constructed in Wen et al. (2020a) to deal with real-world problems with large sizes.

4. Scheduling for both cockpit crew and cabin crew

In this section, we review four representative crew pairing studies that consider both cabin crew and cockpit crew.[1] The problem

[1] In these selected studies, both cockpit and cabin crew are mentioned in areas like problem definition and computational experiments. We thus categorize these studies as for both cabin and cockpit crew.

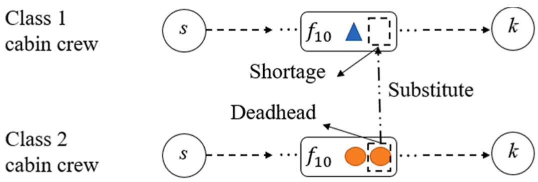

Fig. 5. A typical example of controlled crew substitution.

and model features of these studies are listed in Table 5 and Table 6, respectively. As discussed in Section 2, the operating characteristics of cabin crew and cockpit crew are very different. However, due to the relatively lower payment and the large problem scale, cabin crew is usually assumed to be identical with cockpit crew when conducting scheduling. For example, in Quesnel et al. (2020b), Saddoune et al. (2013), and Erdoğan et al. (2015), cabin crew members are implicitly assumed to be single-qualified. The manpower requirements for cabin crew are thus assumed to be homogeneous, and each flight is needed to be covered by (at least) one (team) pairing. Moreover, none of these studies considers the practical operation of crew substitution for cabin crew. Detailed discussions for each of these selected studies are presented in the following.

In order to improve the decision making of the crew assignment/rostering problem, Quesnel et al. (2020b) study a crew pairing problem in which the preferences of crew members are considered, with the aim of alleviating the deficiency of the rigorous separated two-stage crew scheduling problem to some extent, as well as improving employee's job satisfaction by developing schedules that are more welcomed by crew members. In the study of Quesnel et al. (2020b), six pairing features associated with crew member preferences are identified. Therefore, the objective function of the pairing model developed by Quesnel et al. (2020b) is formulated to encourage the selection of the pairings containing the identified features (i.e., rewards are given). A column generation based solution algorithm is proposed to solve the complex model. Accordingly, a new path resource is designed to handle the complex pairing features for the sub-problem of the column generation, which is transformed into a resource-constrained shortest path problem. In the study of Erdoğan et al. (2015), it is pointed out that although the crew-related cost is the second-largest expenditure for airlines which follows fuel costs, it is the biggest cost component that an airline can control as the crude oil price is usually uncontrollable. Focusing on the crew pairing problem for European airlines, Erdoğan et al. (2015) construct a large-scale mathematical model which considers the specific flight structure, planning horizon, and objectives for a European airline. To be specific, Erdoğan et al. (2015) find that a great percentage of the flights operated by the considered European airline are round-trip flights. An optimization-based heuristic solution algorithm combining large neighborhood search, exact enumerative algorithms and integer programming is developed to solve large-scale problems in Erdoğan et al. (2015). Computational experiments show that the proposed heuristic has the ability to handle monthly problems involving more than twenty thousand flights efficiently. Moreover, the results demonstrate that the round-trip flight structure helps simplify the solution algorithms and facilitates the overall scheduling process (Erdoğan et al., 2015). Saddoune et al. (2013) claim that the crew pairing problem in the aviation industry is often solved by a three-phase method in which a daily problem, a weekly problem, and a monthly problem are solved sequentially. They claim that this heuristic three-phase approach prohibits the repetition of the same flight number in a pairing for the daily pairing problem. As a result, the monthly schedules generated from the daily solutions involves no flight number repetitions. Therefore, Saddoune et al. (2013) develop an alternative methodology which can deal with the flight number repetitions in a single pairing. A complex pairing cost function is applied to approximate the real practice as shown in Eq. (10), which consists of the waiting cost, the deadhead cost, and the guaranteed minimum flying time paid per duty. To be specific, the waiting cost ($g(\delta_w)$) is a function of the waiting duration δ_w for wait period $w \in W_p$. For a deadhead arc $h \in H_p$, its cost is composed of a fixed component γ, together with the deadhead duration δ_h multiplying the unit cost μ. The last part in Eq. (10) represents the guaranteed minimum flying time paid per duty, where v is the payment for each flying hour, V_{min} is the guaranteed minimum flying time paid per duty, and v_d is the total credited flying time in duty $d \in D_p$. The authors find that the solution quality can be enhanced with less computational time when the daily problem and the weekly problem are skipped while the monthly problem is directly solved through a column generation based rolling-horizon approach if an irregular flight schedule is given. On the other hand, for regular flight schedules, better solutions (with lower costs) are obtained if the weekly problem is directly solved without the daily problem due to the fact that flight number repetitions become possible (Saddoune et al., 2013). The computational experiments conducted in Saddoune et al. (2013) show that the with-repetition solutions illustrate less fat than the no-repetition solutions, with a significant average reduction of around 16%. Besides, the percentage of pairings containing flight number repetitions can even reach 100% for some instances, showing the weakness of the no-repetition approach (Saddoune et al., 2013).

$$c_p = \sum_{w \in W_p} g(\delta_w) + \sum_{h \in H_p} (\gamma + \mu\delta_h) + v \sum_{d \in D_p} \max\{0, V_{min} - v_d\} \tag{10}$$

Differently, Medard and Sawhney (2007) distinguish the two types of air crew when constructing pairings. Actually, Medard and Sawhney (2007) solve the crew scheduling problem in a single step by integrating the pairing construction and pairing assignment procedures. Besides, the recovery problem in the operational stage is also considered in Medard and Sawhney (2007). Instead of modelling cabin crew members in a team basis or in an individual basis, a novel concept, named as *crew slice*, is developed by Medard and Sawhney (2007) to satisfy the heterogeneous manpower requirements of different flights. To be specific, the manpower-requirement vector for all flights are decomposed into a set of sub-manpower-requirement vectors (i.e., slices). Then, the flights to be scheduled can be grouped according to the slice category. Accordingly, the pairing problem can be solved within each flight group.

Table 5
Problem features for the literature reviewed in Section 4.

Literature	Home base		Modelling approach		Manpower requirement		Crew substitution	
	Multi-base	Single-base	Team	Individual	Homogeneous	Heterogeneous	Controlled	Not-controlled
Quesnel et al. (2020b)	√		√		√			
Saddoune et al. (2013)	√		√		√			
Erdoğan et al. (2015)		√	√		√			
Medard and Sawhney (2007)	√		Crew slice			√		

Table 6
Model features for the literature reviewed in Section 4.

Literature	Model format	Objective		Flight coverage constraint		Solution approach	
		Cost minimization	Others	Each flight is covered by (at least) once	Specific requirements are considered	Column generation based	Others
Quesnel et al. (2020b)	Set-partitioning problem	√	Constraint penalties	√		√	Rolling horizon
Saddoune et al. (2013)	Set-partitioning problem	√		√		√	Rolling horizon
Erdoğan et al. (2015)	Set-partitioning problem	√		√			Model-based metaheuristics
Medard and Sawhney (2007)	Set-covering problem	√			√	√	Tree search

This method can ensure that the specific manpower requirement for each cabin crew class of each flight can be fully satisfied (Medard & Sawhney, 2007). However, as cabin crew members are bundled within the "slices", the solution flexibility is limited in Medard and Sawhney (2007). In terms of the crew pairing modelling, Medard and Sawhney (2007) not only consider the flight coverage constraint, but also formulate the base maximum workload restriction to make the model developed more realistic.

5. Robust scheduling for cockpit crew

During the tactic planning stage, the airline crew scheduling problem aims to keep the planned crew costs low by removing the slacks in crew schedules, resulting in many tight flight connections. However, flight delays are common in real operations. Tight crew connections can thus be easily disrupted under the uncertain operational environment, causing propagated flight delays or flight cancellations, leading to a significant gap between the planned and operational crew costs. Therefore, airlines are moving from cost-minimization planning to robustness-oriented planning in recent years. As discussed, robust scheduling problems are relatively more complex than the traditional scheduling problems. Therefore, the robust crew scheduling research is mainly based on cockpit crew. We review several representative robust crew scheduling studies in this section[2]. The problem and model features of these studies are summarized in Table 7 and Table 8, respectively.

Uncertainties are inevitable in the daily airline operations, which are incurred by both external and internal factors. It is reported by FAA that, in 2018 and 2019, the direct operating costs (i.e., crew, fuel, maintenance, etc.) induced by flight delay reached 7.7 and 8.3 billion USD[3], respectively. The cost mainly came from two sources: schedule buffers and unforeseen delays. Rather than adopting recovery operations after the happening of disruptions, taking uncertainties into consideration during the airline tactic crew scheduling stage helps obtain more robust solutions to mitigate the negative impacts of disruptions and maintain the feasibility of the original plan as much as possible. However, more computational efforts are required to obtain the solutions. Root delay and propagated delay are commonly considered for robust airline scheduling problems as the measure of robustness. To be specific, propagated delay is commonly referred to the delay caused by the late-arrival of aircraft or the absence of crews. Fig. 6 illustrates the cases under which the propagated delay is incurred. As the propagated delay is induced by either aircraft or crew, in some studies, the two types of propagated delay are considered separately. For example, Yen and Birge (2006) focus on the investigation of the interactions among the potential crew schedules, in which the disruption cost, i.e., the measure of robustness, is formulated as the cost of delays due to crew switching planes. A typical two-stage stochastic integer program is modeled to solve the robust model in which the recourse indicates the disruption cost under different scenarios. Although the authors apply the state-of-the-art set-partitioning solver for the deterministic part, with the size growth of the scenarios considered, the computational burdens become increasingly heavy. A novel

[2] Some studies do not state clearly what type of air crew they are considering. However, the distinctive operating characteristics of cabin crew are not formulated in the models developed by these works. Therefore, we categorize these studies into the "cockpit crew" type.

[3] The detailed information is available at https://www.faa.gov/data_research/aviation_data_statistics/media/cost_delay_estimates.pdf (Accessed on 20 November 2020)

Table 7
Problem features for the literature reviewed in Section 5.

Literature	Crew-induced delay		Modelling approach			Manpower requirement		Flight time characteristics	
	Separate	Integrated	Data-driven	Scenario-based	Worst-case	Homogeneous	Heterogeneous	Considered	Not-considered
Yen and Birge (2006)	√			√		√			√
Chung et al. (2017)		√	√			√			√
Antunes et al. (2019)	√				√	√			√
Sun et al. (2020b)		√	√			√		√	

Table 8
Model features for the literature reviewed in Section 5.

Literature	Model format	Objective		Robust measurement		Solution approach	
		Cost minimization	Others	Expected delay cost	Other cost	Column generation based	Others
Yen and Birge (2006)	Two-stage stochastic program with recourse	√	Disruption cost	Crew-induced		√	Flight-Pair branching
Chung et al. (2017)	Set-covering problem	√	Reserve crew cost	√	√	√	Modified multi-label correcting algorithm
Antunes et al. (2019)	Set-partitioning problem	√	Additional crew costs due to delays	√		√	
Sun et al. (2020b)	Set-covering problem	√	Robustness cost	√	√	√	Problem featured based multi-label correcting algorithm

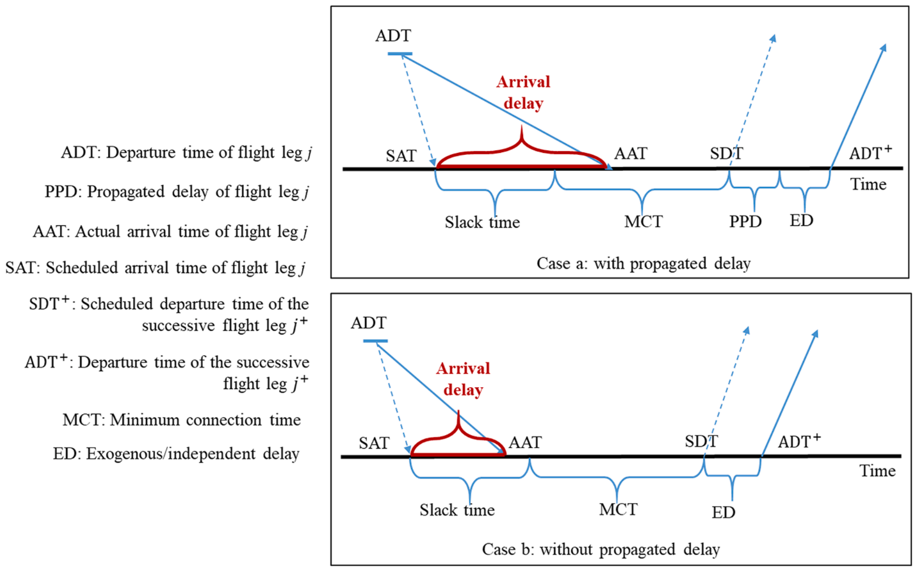

Fig. 6. Illustration of the propagated delay.

algorithm called flight-pair branching is developed to improve the computational efficiency by producing smaller branching trees. It is concluded that significant savings can be achieved if the delay effects on crew schedules and the resulting effects on the entire system are considered during the planning phase. However, this study focuses on a small flight network with a sample of only 100 scenarios of the flying time realizations.

Robust optimization is another main stream to deal with uncertainty. The major advantage of robust optimization is that it is unnecessary to know the distribution information of the random factors, such as root delay and propagated delay. Taking the advantage of robust optimization, Antunes et al. (2019) develop a robust pairing model for airline crew scheduling in which a robust pay-and-credit salary structure for crew is considered. Different from the existing literature, Antunes et al. (2019) not only consider the additional crew cost due to delays, i.e., the increased duty and pairing elapsed time, but also measure the robustness by the flight delay costs due to the propagated delay. The proposed model is converted into a standard set partitioning problem to make it solvable by using the column generation technique. A case study based on a moderate-size real flight network is conducted with the conclusion that a significant reduction of both averages and the variability of delay and disruption costs can be obtained with a small increase in the planned crew cost which is often below 3%.

Although the implementation of robust optimization seems to be easier than stochastic optimization, it is still a challenging task to characterize the uncertainty set to avoid overly-conservative schedules. With the technological advancements of the big data analytics, data-driven robust optimization becomes a prosperous trend for airline scheduling. For example, Chung et al. (2017) incorporate a new machine learning based method into the crew pairing robust optimization model to improve the robustness of the solutions. With the learning ability of the cascading neural network, it is revealed that the arrival delay is correlated with the departure delay as the arrival delay prediction can be improved with the input of the departure delay forecast. It is verified that the machine learning based approach is better than the traditional regression method or ARIMA. In addition, a dynamic reserve crew allocation strategy is further combined with the robust optimization model to help determine the optimal number of reserve crew for the possible disruptions due to propagated delays. It is critical for airlines to maintain the feasibility of flight schedules and reduce disruption costs. However, in Chung et al. (2017), the uncertainty is analyzed under a discrete form with no considerations of the flying time characteristics under different circumstances.

Inspired by the results of Chung et al. (2017), Sun et al. (2020b) investigate further into the characteristics of the flying time and verify the interdependency of the departure time and arrival time in a continues form. Based on data analytics, Sun et al. (2020b) find that, for more than 23% flights explored, the expected flying times are significantly affected by its actual departure times. Accordingly, the flying time of Flight f is modeled into a regression relationship as follows:

$$FT_f(T) = \mu_f(T) + \sigma_f(T)\epsilon.$$

Here, T is a random variable, which represents the departure time of Flight f. Given $T = t$, $\mu_f(t) = E\left(FT_f(T)\middle|T = t\right)$ is the regression mean function, while $\sigma_f(t) = Var\left(FT_f(T)|T = t\right)$ is the regression variance function. ϵ is a white noise. Fig. 7 illustrates a specific case when the interdependency between the departure time and the flying time for Flight f follows a linear function.

In addition, in Sun et al. (2020b), a novel robustness measure is introduced, which is composed of both the expected departure and arrival delays and the overtime cost for the crew members due to flight delays. It is somehow similar with the additional crew cost in Antunes et al. (2019), but in fact they are different. First of all, in Antunes et al. (2019), it is assumed that the root delay and propagated delay are uncorrelated. However, in Sun et al. (2020b), with the data analytics by using the heteroscedastic regression model, it is verified that the flying time is affected by both the expected value of departure time and its variability. In other words, the propagated delay is interacted with the root delay when the timing of the departure and arrival has a great impact on the flight delay. With the considerations of both the first and second moments of the flight time, the over-estimates or under-estimates on the propagated delay can be greatly eliminated. Experiment results show that a significant improvement in the reliability of the crew pairings derived can be achieved with a slight increase of the total basic operations cost.

Except for the robust measurements aforementioned, different robust optimization criteria can be explored for solving robust crew scheduling under distinct situations. For instance, min–max regret approach was applied by Ng et al. (2017) for solving a robust aircraft sequencing and scheduling problem. The principle of min–max regret approach is to find the solution with the minimum regret value of the worst-case under different scenarios, i.e., $\min_{X\in\Omega} Regret_{max}(X)$, where X is a feasible solution belonging to the feasible set Ω. A regret value is defined as the deviation from the optimal value under a given scenario $s \in S$, i.e., $Regret(X, s) = F(X, s) - min_{X\in\Omega}F(X, s)$. For crew scheduling problems, the regret value can be defined as cost-oriented and time-oriented according to the specific preference for the decision maker. Thus, a well-designed iterative algorithm is essential to solve such a worse case based approach efficiently, which becomes even more challenging when the problem scale increases.

6. Recovery for cockpit crew

In this section, we review four representative crew recovery studies. Similar to the robust scheduling studies, the recovery problems are also mainly based on cockpit crew[4]. The problem and model features of these studies are listed in Table 9 and Table 10, respectively. As discussed in Section 5, robust plans help mitigate the risks of severe disruptions. However, in the real world, the daily disruptions cannot be fully avoided even with the support of robust plans. This is because that uncertainties cannot always be forecasted as the disruptions may come from both exogenous and endogenous factors. For example, due to bad weather and air traffic control, the flow rate reduction and temporary closure of airports are incurred for safety considerations, which directly affects the ongoing flights and the corresponding crew schedules. Once the disruption happens, airlines have to make a recovery plan with the minimum recovery cost in a short time. For instance, Lettovský et al. (2000) proposes an optimization-based approach for the airline crew recovery problem. The recovery actions proposed in Lettovský et al. (2000) include crew swaps, standby/reserve crew and deadheading. Fig. 8 displays an example of crew swapping.

[4] Some studies do not state clearly what type of air crew they are considering. However, the distinctive operating characteristics of cabin crew are not formulated in the models developed by these works. Therefore, we categorize these studies into the “cockpit crew” type.

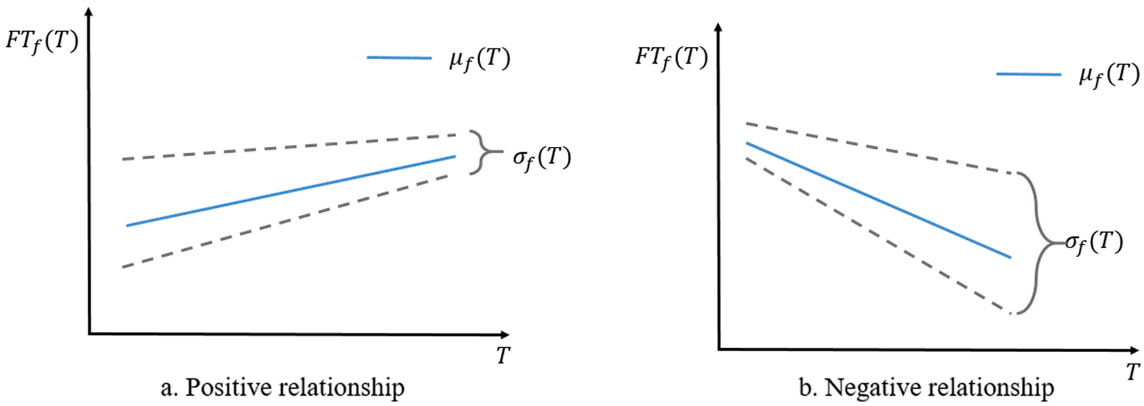

Fig. 7. Illustration of the interdependency between the departure time and the flying time.

Table 9
Problem features for the literature reviewed in Section 6.

Literature	Recovery actions		Modelling approach		Manpower requirement		Recovery horizon	
	Flight cancellation & deadheading	Others	Separate	Integrated	Homogeneous	Heterogeneous	Single	Multiple
Lettovský et al. (2000)	√		√		√		√	
Abdelghany et al. (2008)	√			√	√			√
Petersen et al. (2012)	√			√	√		√	
Arıkan et al. (2017)	√	Cruise speed control		√	√		√	

Table 10
Model features for the literature reviewed in Section 6.

Literature	Model format	Objective		Scope of Recovery		Solution approach	
		Cost minimization	Others	Disrupted flights	Others	Column generation based	Others
Lettovský et al. (2000)	Set covering problem	√			Disrupted crews		Branching techniques
Abdelghany et al. (2008)	Mixed integer program	√	Delay cost	√			Greedy optimization strategy
Petersen et al. (2012)	String-based model	√	Aggregate passenger delay	√	Retiming flights	√	Row generation
Arıkan et al. (2017)	Conic quadratic mixed integer program	√	Fuel cost / passenger disruption cost	√	Aircraft and crew networks limitation		Partial network generation algorithm

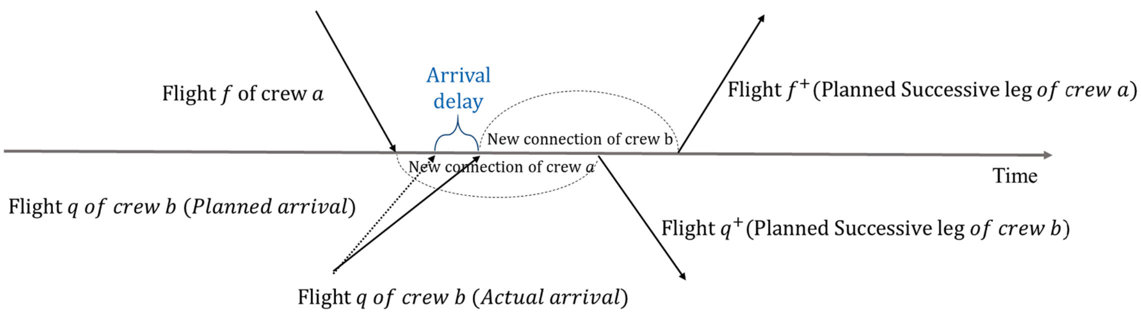

Fig. 8. Illustration of crew swapping.

The optimization objective proposed by Lettovský et al. (2000) is to minimize the overall crew assignment cost, flight cancellation cost and deadheading cost. As the full-scale optimization is ruled out due to the highly efficient computational requirement for the real-time recovery plans, the premise to optimize the crew recovery problem is the determination of the recovery horizon and the scope of recovery. The recovery horizon is usually exogenous, and the objective of the recovery problem is to bring the operations back to the schedule by the end of the recovery horizon. Lettovský et al. (2000) proposes a deadhead selection heuristic by categorizing deadheading options, e.g., multiple assignments, out of flying time, catching up and repositioning, to realize the reduction of the recovery problem size. Then the crew recovery problem is formulated by an integer program. A primal–dual subproblem simplex method combined with the customized three-stage branching strategy is developed to solve it. However, the proposed optimization-based method is only applicable for small to medium sized disruptions.

In real-time airline operations, the interdependency among different entities indicates that the optimal recovery actions of the crew members will affect the recovery plans for the aircraft and passengers involved. Obviously, global optimization cannot be realized by separated or sequential decisions. In recent years, more researchers explore the interdependency among the recovery actions of crew, aircraft, passengers and schedules. Abdelghany et al. (2008) develop an integrated airline recovery approach within a rolling horizon modelling framework. Different from the traditional single-period recovery problem, Abdelghany et al. (2008) introduce a new objective to realize the trade-off between the delay savings and the number of flights with swapped resources. To the best of our knowledge, it is the first academic study to analyze the impact of the integrated recovery plans on flight delays in a dynamic network operational environment. Abdelghany et al. (2008) argue that it is critical for the airline to seek for the balance between the number of swapped resources and flight delay/cancellation savings to guarantee the quality-of-life of its crew members. But the problem setting in Abdelghany et al. (2008) is based on the deterministic environment and the greedy optimization strategy, which limits its applications to large-size problems in real situations. Petersen et al. (2012) further incorporate the schedule recovery into the integrated airline recovery problem by retiming the departure time. The full integrated recovery problem is based on a string-based model, in which column generation techniques are applied for string generation, followed by a Benders decomposition scheme in which the schedule recovery model is the master problem and the other recovery models are subproblems. Petersen et al. (2012) control the recovery scope by limiting flights disrupted from different resources. Besides, instead of using the traditional uniform flight copy approach, an event-driven delay approach is developed to reduce the total generated flight strings. Although the authors made great efforts on reducing the scope of the recovery operations, it is still challenging to solve the full integrated problem. In particular, repairing the crew duty network is the major bottleneck, as the decision maker has to identify a tradeoff between the computational tractability and the quality of the crew network connectivity by considering more information along with a longer time window. In fact, preprocessing the scope without sacrificing the optimality before recovery is crucial to help airlines to obtain a cost-effective recovery plan in real time.

In addition to the traditional recovery actions for crew and aircraft, Arıkan et al. (2017) further investigate the impacts of cruise speed control on the recovery of delayed flights. With the information shared among airlines and airports, following the slot allocation guideline provided by the International Air Transport Association (IATA), for the situations with limited slot resources, an airport can allocate the slots to airlines after coordination. Arıkan et al. (2017) propose a novel integrated recovery model for a flight network in which all the entities are represented in the same manner. The objective is to identify a tradeoff between the total assignment cost, additional fuel cost and passenger delay cost. By taking the advantage of the activity-on-node network, the departure/arrival times and cruise speeds are modeled as continuous variables which facilitate the reduction of the solution space. Different from the existing studies, a novel partial network generation algorithm is proposed to further help eliminate the infeasible recovery actions before solving the optimization model. The impacts of the problem size control and the length of the recovery horizon on the solution optimality are discussed. The results indicate that the tradeoff between the computational complexity and the recovery quality cannot be avoided. Cruise speed control is a good recovery action to reduce flight delays and facilitate more passenger connections with the increasing disrupted flights. However, to guarantee the service quality as well as the profit, how to determine the optimal recovery horizon and coordinate among different entities to realize different recovery actions is an open question which needs deeper explorations.

7. Future research agenda

Based on the review of some prior studies presented above, in this section, we propose a future research agenda for the airline crew scheduling problem which is summarized in Table 11.

7.1. Disruption management for cabin crew

Due to the diverse distinctive operating characteristics of cabin crew, the problem scale and complexity for the scheduling optimization problem for cabin crew are much higher than those for cockpit crew. Therefore, the existing cabin crew scheduling studies mainly concentrate on minimizing operating costs without disruption considerations. That is, little attention has been paid to improve the solution robustness for cabin crew schedules constructed during the tactic planning stage or the recovery solutions during the operational stage. However, the various uncertainties in the operations environment of the aviation industry are unavoidable, bringing great challenges for cabin crew management. Therefore, it is of great value to explore the disruption management strategies for cabin crew. As each flight might require different numbers of cabin crew members regarding each crew class, exploring how to apply the commonly used robustness enhancement strategies for cockpit crew pairings (like crew swaps) to cabin crew is a promising future research direction. Moreover, applying the specific operations characteristics of cabin crew, like crew substitution, to develop a new

Table 11
Summary of the future research agenda.

Areas		Topics	Examples
Disruption management for cabin crew		Robust cabin crew scheduling	Crew swaps among cabin crew members
		Recovery for cabin crew	Crew substitution recovery operations
The impacts of COVID-19 on the airline crew scheduling problem		The special scheduling problem under/after pandemic	Special manpower skills Disrupted manpower resource Recovery problem
The impacts of blockchain technologies on the airline crew scheduling problem	Blockchain based information sharing for crew operational risk management	Airline operational risk management	Information sharing Cooperative operations Information security
	Blockchain based information updating and risk perception for crew recovery	Crew recovery in a cooperative operating mode	Recovery strategies with quick response Dynamic and stochastic operating environment the operational information updating and risk forecasting

robustness enhancement strategy is an interesting area. For crew recoveries, as cabin crew members are allowed to substitute others under some conditions, it is valuable to investigate how to utilize crew substitution to bring the disrupted flights back to the schedule as soon as possible. However, as cabin crew members shall be considered with their classes and the heterogeneous manpower requirements on different flights, how to obtain the optimal recovery solutions efficiently is a critical challenge. As we all know, airlines usually need to find recovery solutions within a short time (e.g., a couple of hours). Therefore, efficient solutions algorithms are needed for cabin crew recovery operations to reduce the negative impact of disruptions as fast as possible. More importantly, the fast development of advanced information technologies (like big data and Intelligent Transport Systems) brings new opportunities for airlines to improve the cabin crew recovery decisions. For example, when the crew swap strategy is applied, the airline can select the most appropriate cabin crew member to swap by evaluating the delay probability of his/her scheduled flight through analyzing a huge amount of real-time data.

7.2. The impacts of COVID-19 on the airline crew scheduling problem

The existing airline crew scheduling problems have considered various disruption sources like crew absence and flight delays. However, the recent widespread of COVID-19 brings new challenges for the area (Amankwah-Amoah, 2020). For example, to satisfy the governmental requirements, special training (e.g., sanitation operations) is required for flight crews. Some countries, like China, impose a great penalty on airlines which fail to satisfy the epidemic prevention requirements and bring the virus in. Therefore, it is important to consider the related manpower skills in the airline crew scheduling problem during the pandemic, especially for the flight routes to and from risky areas. New optimization models are thus needed. For instance, during the period of the COVID-2019 pandemic, crew members' absence due to the self-isolation is essential to be considered for the optimization modelling, in which the flexibility of the crew scheduling is inevitably restricted. In addition, whenever there is a confirmed case during a flight, the original crew scheduling will be disrupted as the corresponding crew members have to be isolated for a certain period for medical observation. Moreover, in case an overlong rest time is involved in the crew scheduling, extra stay time may be incurred for necessary testing and medical observation. Therefore, how to model the situations of the absence of the specific crew members for a certain time period so as to realize cost-effective recovery plans for the following flights in the low-risk areas is critical and challenging when developing the mathematical optimization models. It is also challenging to model a robust crew scheduling optimization framework with the consideration of the potential risks caused by the passengers coming from high-risk areas and multiple rest periods outside crew base.

Moreover, it is a promising direction for airlines to improve their schedules by incorporating the risk data into the planning framework. For instance, through advanced data analytics methodologies (like neural networks learning algorithms), airlines can evaluate the risk level of flight origins/destinations, thus reducing or avoiding the flight connections involving risky areas. Besides, a majority of global airlines cancelled their domestic and international flights due to the pandemic. It is reported by ICAO that, throughout 2020, the number of seats offered by airlines is estimated to reduce by 51%, while the overall decrease of passengers would be 2877 to 2888 million, and the impacts are forecasted to last to 2021 (ICAO, 2020). Therefore, many flight crew members lost their jobs or took a no-pay leave. According to CBC News, Air Canada dismisses more than 5,100 members of its cabin crew amid a steep fall in travel demand[5]. Air New Zealand lays off a third of its employees and Qantas Airways place 20,000 workers on leave according to Reuters[6]. The manpower resource of airlines is thus disrupted significantly. It will thus be an extremely challenging task to carry out crew planning operations during the recovery of the aviation industry.

[5] https://www.cbc.ca/news/canada/british-columbia/more-than-5–100-air-canada-flight-attendants-to-be-laid-off-amid-massive-covid-19-slowdown-1.5504051 (Accessed on 4 December 2020)

[6] https://www.reuters.com/article/us-health-coronavirus-australia-factbox/factbox-layoffs-in-corporate-australia-new-zealand-as-coronavirus-crisis-deepens-idUSKCN21Y05H (Accessed on 4 December 2020)

7.3. The promising application of blockchain technologies in airline crew operations

I. ***Blockchain based information sharing for crew operational risk management***

From the review presented above, it is seen that the existing airline crew scheduling problem is usually solved by the airline itself. The efficient and effective cooperation among multiple agents, i.e., air traffic control, airports, airlines, is limited due to the lack of the information sharing. However, with the development of the big data analytics, the cooperative operation among multiple agents is a growing trend for the aviation industry (Choi et al., 2019; Fairbrother et al., 2020), which facilitates the operational risk management of airlines. For example, the development of the Airport Collaborative Decision-Making (A-CDM) is a promising solution to help realize information sharing and cooperative operations among diverse related parties. However, information security is vital in the aviation industry. The blockchain technology can thus play a critical role to guarantee the security and privacy issues during the information sharing among multiple agents, such as the crew information, flight manifests, and passenger data. Based on information sharing, the blockchain technology will contribute to establishing an integrated database and form a cooperative operational agreement. This will further help enhance the quality of the analyses in terms of the interactive factors among crew, aircraft, airports, and air traffic control departments during the airline network planning stage, e.g., aircraft maintenance routing, crew scheduling, and slot allocation. It will be a promising but challenging future research direction to characterize the interactions between the crew operations decision making and the delay status via big data analytics, by which a data-driven optimization model with crucial robustness measures can be built to mitigate the operational risks, such as delay and flight cancellation, under high uncertain environment (Khan et al., 2019a, 2019b; Wang et al., 2020).

II. ***Blockchain based information updating for time–space resources coordination***

Real-time information updating is also crucial to deal with airline schedules disruptions in real practice, which has received little attention in the existing literature. There is no doubt that disruptions cannot be completely avoided in the real world which is full of uncertainty and volatility (Sun et al., 2015, 2018, 2020b). Disruptions bring considerable damages to service operations such as the aviation industry (Choi, 2020). The existing literature demonstrates that the recovery strategies with quick response can greatly contribute to the airline operating efficiency and performance (Choi et al., 2019). Instead of modelling the crew recovery problems under a static environment, making the crew recovery decisions with the consideration of a dynamic and stochastic operations environment is much more in line with the real world, and the solutions generated in this way are more reliable and useful. For example, the restrictions on the flying time and working hours during each duty and pairing may incur potential disruptions of the successive flights due to exogenous factors from the airport side. Driven by the advanced information technologies, such as blockchain technology, the real-time information sharing platform can help predict the delay risks due to the uncertainties coming from the airport side and the delay propagation in the overall airline network. It will further facilitate the design of optimal recovery strategies in a dynamic and stochastic environment by analyzing various potential operational risks, like the infeasibility of crew recovery decisions due to the violation of working rules and regulations (e.g., the maximum working hours). In the future, it will be a very promising research direction to study the crew recovery problem in a cooperative operating mode with the operational information updating and risk forecasting in the airline network. However, how to design and model the strategies for multi-party cooperative operations, in terms of information sharing and resources coordination, is essential to formulate the mathematical optimization for real-time crew recovery.

In conclusion, from the analyses presented above, it is seen that the disruption management for cabin crew, the impact of COVID-19, and the information sharing/updating among diverse participants, together with the application of advanced information technologies (e.g., big data analytics, blockchain, and Intelligent Transport Systems) are promising and valuable future research topics for airline crew scheduling problems. Moreover, it is worthwhile to notice that these research directions are interrelated with each other and can serve a common objective of improving the disruption management efficiency. It is also worthwhile to note that the application of advanced information technologies can play a pivotal role in alleviating the negative impacts brought by the uncertain and volatile operations environment in the aviation industry.

8. Concluding remarks

With the growing importance of the air transportation industry for the global economic development, the airline scheduling problem has become one of the most crucial but challenging tasks for modern airlines due to the large problem scale and high problem complexity. Airlines are operating with two distinct types of air crew. They are cockpit crew and cabin crew. These two crew types are very different in operating characteristics, which greatly affects the corresponding scheduling problems. For example, cockpit crew is single-qualified while cabin crew is mixed-qualified. The manpower requirement for cockpit crew is homogeneous within an aircraft type. However, the manpower configuration for the multi-class cabin crew is heterogeneous across aircraft types and cabin layouts. Additionally, according to the planning stage, the airline crew scheduling problem can be classified as tactical planning problems and operational planning problems. To be specific, the tactical planning is conducted weeks or months before the actual operations. Traditionally, cost-minimization is the focus of the tactical planning problem. In recent years, due to the highly volatile operating environment, airlines are moving from the cost-minimization scheduling to the robust scheduling, with the aim of enhancing the solution robustness to better hedge against the potential disruptions in real operations. On the other hand, in the operational stage, recovery is used to bring the disrupted operations back to schedule in order to alleviate the negative impacts of various disruptions that have happened. Realizing the significance of the airline crew scheduling problems and a lack of review on the modelling and algorithmic advancements in terms of each crew type and planning stage, we develop this paper to examine the related literature from four aspects: the scheduling for cabin crew, the scheduling for both cabin crew and cockpit crew, the robust scheduling for cockpit crew, and the recovery for cockpit crew. We summarize the key findings as follows.

First, the scheduling studies concentrating on improving the decision making for cabin crew are reviewed. We have highlighted the unique model features for cabin crew scheduling problems. To be specific, it is identified that in addition to the set-covering or set-partitioning modelling approach, a pure network model can also be applied to solve small-scale problems. Besides, side constraints can be proposed to improve the pairing solutions for cabin crew. On the other hand, if the distinctive operating characteristics of cabin crew (e.g., multiple classes, mixed-qualification, heterogeneous manpower requirements, crew substitution) are considered, the problem scale will increase significantly, making the column-generation based solution approaches less applicable.

Second, we have examined the studies that consider the scheduling for both cockpit crew and cabin crew. Actually, the cabin crew's unique operating features are often ignored to make the problem tractable. However, a concept named as crew slice can be applied to formulate the specific manpower requirements for each class of cabin crew and cockpit crew on each individual aircraft. Besides, a rolling horizon approach which divides the airline crew scheduling problem into a daily problem, a weekly problem, and a monthly problem that are solved sequentially can help reduce the problem complexity.

Third, some typical studies on robust scheduling of cockpit crew are reviewed. It is found that there is no standard and best robust measurement for crew scheduling. However, the importance of decision makers to pursue the tradeoff between the traditional operating cost and the investment cost for the future potential disruptions has been revealed. With the development of the big data analytics technology, risk forecasting and analysis for the interactive relationship among different types of flight delays is a trend to help explore new robust measurements for more reliable and flexible plans without increasing the complexity of the solution algorithm.

Fourth, we have further examined the studies on crew recovery which serves for the situations when severe disruptions have happened during the operations. Different from the planning stage, the recovery actions usually take place in real-time which needs quick response with low recovery costs. Although there are many studies focusing on both costs and time efficiency of the recovery solutions, it is still challenging to guarantee the service quality as well as the profit, to determine the optimal recovery range, and to coordinate different parties to realize different types of recovery actions.

After investigating the literature and examining some related models & solution algorithms, we have established a future research agenda which includes the disruption management for cabin crew, the impact of COVID-19, and the impact of blockchain technology. It is believed that this paper can provide useful information to both practitioners and academics on the modelling and algorithmic advancements in the airline crew scheduling problems.

CRediT authorship contribution statement

Xin Wen: Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Formal analysis, Visualization, Project administration. **Xuting Sun:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Formal analysis, Visualization. **Yige Sun:** Writing - review & editing, Formal analysis, Visualization. **Xiaohang Yue:** Formal analysis, Supervision.

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