UNIVERSITÉ DE MONTRÉAL

# OPTIMISATION INTÉGRÉE DES ROTATIONS ET DES BLOCS MENSUELS PERSONNALISÉS DES ÉQUIPAGES EN TRANSPORT AÉRIEN

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# DÉDICACE

*À mes parents, Maliheh et Mojtaba,*
*À mon frère, Arash,*
*À ma soeur, Sara,*
*de tout mon cœur.*

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*"It is impossible to be a mathematician without being a poet in soul." Sofia Kovalevskaya*

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## RÉSUMÉ

Le problème de la construction des horaires d'équipage pour les compagnies aériennes consiste à assigner un groupe d'équipage à un ensemble planifié de segments de vols. Ce problème doit également respecter des règles de travail définies par la convention collective et les autorités du transport aérien. Le problème de la construction des horaires d'équipage a reçu une attention particulière en recherche opérationnelle car après le carburant, le coût des équipages constitue la plus grande dépense des compagnies aériennes. En raison de la grande taille du problème et de la complexité des règles de travail, ce problème est traditionnellement traité en deux étapes qui sont résolues séquentiellement : la *construction de rotations* et la *construction de blocs mensuels*. La première construit un ensemble de rotations réalisables à coût minimum afin que chaque vol prévu puisse être réalisé par un équipage. Les rotations réalisables sont celles juxtaposant des vols conformément aux règles de la convention collective entres les employés et la compagnie aérienne. La deuxième étape construit des blocs mensuels pour les membres d'équipage en combinant les rotations trouvées précédemment avec les repos, et d'autres activités. Chaque bloc mensuel doit satisfaire certaines règles définies par le contrat de travail.

Les membres de l'équipage sont divisés en deux groupes selon leurs rôles et leurs responsabilités : *les personnels du poste de pilotage* et *les personnels de la cabine des passagers*. Les pilotes, les copilotes et les mécaniciens de bord font partie du personnel du poste de pilotage. Le personnel du poste de pilotage est qualifié pour piloter un avion ou une famille d'avions. Le capitaine de cabine et les agents de bord font partie des membres de la cabine des passagers. Par le passé, les chercheurs se sont concentrés sur la réduction des coûts associés au personnel du poste de pilotage car leurs salaires sont plus élevés que ceux des membres de la cabine des passagers. Dans cette thèse, nous nous concentrons uniquement sur le personnel du poste de pilotage.

La construction des blocs mensuels varie pour chaque compagnie aérienne. Toutefois, on peut classer les méthodes en deux catégories : la construction des *blocs anonymes (bidline)* et la construction des *blocs personnalisés*. Pour les blocs anonymes, les horaires sont construits de manière à couvrir toutes les rotations sans connaître les préférences des employés. Les blocs sont ensuite présentés aux membres d'équipage qui sélectionnent les blocs qu'ils veulent faire. Contrairement aux blocs anonymes, les blocs personnalisés tiennent compte des préférences des membres de l'équipage. La construction de ces blocs se fait selon deux objectifs : le *rostering* et les *blocs personnalisés avec séniorité (preferrential bidding)*. Le premier maximise

la satisfaction globale des membres d'équipage sans considérer la séniorité. Le second priorise la satisfaction des membres ayant le plus d'ancienneté.

D'un point de vue historique, la construction des blocs anonymes a été l'approche la plus utilisée par les compagnies aériennes nord-américaines alors que la construction des blocs personnalisés a été plus fréquente en Europe. Cependant, les blocs personnalisés sont aujourd'hui une approche de planification utilisée par de plus de compagnies aériennes nord-américaines car ils sont plus avantageux à la fois pour les membres de l'équipage et les compagnies aériennes.

Par le passé, le problème de construction des rotations et le problème de construction des blocs mensuels ont été modélisés indépendamment. Bien que cette approche réduise la complexité du problème, elle ne considère pas les contraintes de construction de blocs mensuels lors de la construction des rotations. Ce faisant, il n'est pas possible de garantir une solution optimale pour tous les membres de l'équipage.

Plus récemment, des chercheurs ont commencé à intégrer ces problèmes. Le problème de construction intégrée de rotations et de blocs mensuels anonymes pour les pilotes a été étudié par Saddoune et al. Cependant, au meilleur de nos connaissances, il n'existe pas de littérature sur le problème d'intégration de construction des rotations et des blocs mensuels personnalisés.

Le premier objectif de cette thèse est de présenter une revue de la littérature sur le problème de construction des horaires d'équipage en transport aérien. De plus, nous présentons un modèle mathématique et une approche de résolution pour le problème séquentiel de construction des blocs mensuels personnalisés. Au meilleur de notre connaissance, aucun modèle permettant de prendre en compte les préférences des pilotes n'a été introduit dans la littérature. Nous avons également observé que peu de chercheurs comparent leurs méthodes sur les mêmes données. Nous proposons donc un ensemble d'instances ainsi qu'un générateur de préférences qui est disponible en ligne pour des fins de comparaison.

Dans le deuxième objectif de cette thèse, nous considérons le problème intégré de construction des rotations et des blocs mensuels personnalisés. Nous proposons un algorithme heuristique qui construit simultanément des horaires mensuels pour les pilotes et copilotes, tout en respectant les préférences personnelles et les contraintes de sécurité. L'algorithme proposé alterne entre les problèmes de construction des horaires des pilotes et des copilotes afin d'obtenir des rotations similaires, même lorsque les blocs mensuels sont différents.

De plus, en raison des perturbations qui arrivent souvent durant l'opération, nous nous sommes intéressés à développer un algorithme permettant d'obtenir une solution robuste ;

c'est-à-dire que nous minimisons la propagation de la perturbation d'un premier vol aux autres vols et aux autres membres d'équipage.

La troisième contribution de cette thèse vise à satisfaire cet aspect. Pour ce faire, nous résolvons le problème de mise à jour des blocs mensuels simultanément pour les pilotes et les copilotes. Nous visons à maintenir les services de vols et les rotations en commun pour les pilotes et les copilotes dans les solutions de mise à jour. Nous proposons ainsi un algorithme heuristique qui alterne entre le problème de mise à jour des horaires mensuels des pilotes et des copilotes.

Pour résumer, cette thèse étudie le problème de construction intégrée des blocs mensuels personnalisés pour les membres de l'équipage. Nous nous concentrons à la fois sur la planification et sur la mise à jour des blocs mensuels.

## ABSTRACT

The airline crew scheduling problem assigns a group of crew members to a set of scheduled flights. This scheduling problem should respect also a set of safety regulations and collective conventions. The airline crew scheduling has received special attention in Operations Research because after fuel, the cost of crew members is the second largest cost for airlines. Due to complexity, traditionally researchers divided this problem into two steps which are solved sequentially: *crew pairing* and *crew assignment*. The former constructs a set of minimum cost anonymous feasible pairings for covering the scheduled flights while pairing regulations are taken into account. The latter combines the anonymous pairings with vacations, pre-assigned activities, and rest periods over a planning horizon (usually a month) to form new schedules for crew members while satisfying safety regulations.

Crew members are divided into two groups based on their roles and responsibilities: *the cockpit crew members* and *the cabin crew members*. Cockpit crew members are composed of the pilot (captain), copilot (first officer), and flight engineer (for large fleets). The cockpit crew members are qualified to fly one or a family of aircraft types. The cabin crew members are the cabin captain and the flight attendants. Because cockpit crew members are paid substantially higher than cabin crew members, most of the literature has focused on cockpit crew members. In this thesis, we also focus on cockpit crew members composed of pilots and copilots.

Despite crew pairings problem which always aims at constructing anonymous pairings, there are two general approaches that airlines consider when solving the crew assignment problem: constructing *bidline schedules* or *personalized schedules*. Bidline schedules are anonymous schedules for which the crew preferences and needs are not taken into account. After constructing bidline schedules for crew members, the airlines announce them to the crew members and crew members select the bidlines according to seniority order. In contrast to bidline schedules, personalized schedules consider crew member's preferences and needs for constructing and allocating the schedules. There are two general ways for constructing personalized schedules: *rostering* and *seniority-based*. The former favors providing a maximum global satisfaction for crew members and does not take crew members seniority into account. The latter prioritizes satisfaction of more senior crew members to the junior ones.

From a historical point of view, bidline scheduling has been the most common approach at North American airlines whereas personalized scheduling has been more common in Europe. However, personalized schedules are now becoming a common scheduling approach at

american airlines by offering advantages for both crew members and airlines.

Each of the crew pairing problem and crew assignment problem were modeled independently. This traditional sequential approach reduces the complexity of crew scheduling problem but does not guarantee a global optimum solution for crew members because the constraints of monthly schedules are not taken into account when the pairings are being constructed.

More recently, researchers have started to study the integration of the crew pairing and crew assignment problems. The problem of integrated bidline scheduling for pilots has been studied by Saddoune et al. However, integrated personalized crew scheduling for pilots and copilots simultaneously has not been the subject of study so far.

The first objective of this thesis is to present an extensive review of literature about airline crew scheduling problem. In addition, in the context of sequential scheduling approach, we present a mathematical model and solution approach for personalized pilot assignment problem. To the best of our knowledge, this personalized assignment model that takes into account the pilots preferences has not yet been introduced in the literature. Furthermore, we observed that researchers frequently do not compare their methods on the same data due to the lack of access to common data sets. Therefore, we made all the data sets and crew preference generators available online which will allow other researchers to do so.

As the second objective in this thesis, we consider the integrated personalized crew scheduling problem that simultaneously constructs monthly schedules for pilots and copilots while respecting the personal preferences and safety constraints. In addition, we are interested to maintain the robustness of the crew schedules due to the real-life perturbations that arrive while the planned schedules are being operated. At the operational level, the pilots and copilots must have similar pairings when possible to prevent the propagation of delays throughout the schedules. We present a heuristic algorithm that alternates between the pilot and copilot scheduling problems in order to obtain similar pairings even when the monthly schedules are different.

In real life, various disruption sources such as weather conditions may result in delaying or canceling the scheduled flights. These delayed or canceled flights will affect the crew schedules. Due to delay propagation, robust crew recovery problem is very significant. As the third contribution of this thesis, we solve the recovery problem simultaneously for pilots and copilots where the planned schedules are constructed using personalized scheduling approach. We aim at keeping the duties and pairings in common during the recovery solution process. This aim is satisfied by considering heuristic algorithm that alternates between pilots and copilots recovery problems. The re-scheduled flights are considered to be given as an input data.

To summarize, this thesis studies integrated personalized crew scheduling problem, in both planning and operational level, which simultaneously constructs/recovers monthly schedules for both pilots and copilots.

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# CHAPITRE 1 INTRODUCTION

L'industrie du transport aérien et ses opérations ont été une préoccupation majeure de la recherche opérationnelle depuis l'avènement de l'ère du jet à la fin des années 1950. Cette industrie est devenue une force économique importante de par ses propres opérations, mais également par son impact sur les industries liées comme le tourisme et la construction des avions. Les revenus liés à l'industrie du transport aérien eux-mêmes proviennent principalement des billets de passagers, tandis que les coûts comprennent les frais d'avion, de carburant, d'équipage et de personnel au sol. Le profit total est une fonction complexe de toutes les opérations. Les données de l'Association du transport aérien (2008) indiquent que le plus grand coût administratif concerne les frais de carburant, et que le deuxième concerne les coûts d'équipage (23,4 %) (Belobaba et al., 2012). Minimiser les coûts d'équipage est donc une tâche essentielle dans l'industrie compétitive du transport aérien aujourd'hui, et étant donnée la masse salariale impliquée, même une petite réduction peut contribuer à des économies importantes. De plus, l'apparition récente de compagnies aériennes à bas prix a augmenté la pression à fournir des billets abordables et a remis l'accent sur l'importance de réduire les dépenses. En conséquence, le problème des horaires d'équipages du transport aérien a dernièrement reçu beaucoup d'attention à la fois dans l'industrie et la recherche académique.

La construction des horaires d'équipage d'une compagnie aérienne consiste à affecter des membres d'équipage à un ensemble de vols en satisfaisant les règles de convention collective et au sécurité de travail. Les restrictions complexes du problème d'horaires d'équipages en font l'un des plus difficiles dans l'industrie du transport. Nous expliquons par la suite la terminologie que nous utilisons dans nos discussions, puis nous offrons une brève description de chaque étape de processus de décision en transport aérien.

## 1.1 Définitions et concepts de base

- *Segment de vol* : Un vol sans escale. Chaque segment de vol est spécifié par cinq caractéristiques : le numéro de vol, l'aéroport d'origine, l'aéroport de destination, l'heure de départ et l'heure d'arrivée.
- *Deadhead (vol de repositionnement)* : Un segment de vol dans lequel un membre d'équipage vole en tant que passager à des fins de repositionnement.
- *Service de vol (SDV)* : Une séquence de vols consécutifs (et/ou deadheads) correspondant à une journée de travail pour un membre d'équipage. Deux SDV consécutifs doivent commencer et se terminer dans le même aéroport. Des SDV sont séparés par une escale de nuit

(layover).

- *Escales de nuit (layover)* : Une période de repos (un arrêt de nuit) entre les SDV qui dure généralement au moins dix heures.
- *Rotation* : Une séquence de SDV et layovers pour un membre d'équipage non spécifié qui commence et se termine à une base. Dans les problèmes à court- et moyen-courriers, les rotations durent généralement d'un à cinq jours ; dans les problèmes de long-courriers, des rotations plus longues sont autorisées.
- *Les rotations réalisables* : Celles dont la juxtaposition des segments de vols est conforme aux règles de la sécurité aérienne, aux règles d'opération de la compagnie et aux règles contenues dans les conventions collectives entre les employés et la compagnie aérienne.
- *Base* : Un grand aéroport. Chaque membre d'équipage est associé à une base, ce qui signifie que toutes ses rotations doivent commencer et se terminer dans cet aéroport.
- *Temps écoulé (elapsed time)* : La période de temps total durant une rotation entre le départ de la base d'un membre d'équipage et son retour, aussi appelé Time Away From Base (TAFB).
- *Temps de vol crédité dans un SDV* : Le temps de vol actif plus un certain pourcentage de temps de vols de repositionnement (typiquement 50%).
- *Bloc mensuel (bloc)* : Une séquence de rotations séparées par du temps de repos qui couvre un horizon de temps donné (généralement un mois de planification normalisée). Dans ce document, le terme *bloc* se réfère à un bloc mensuel.
- *Temps de briefing* : Une période de temps avant le début de chaque SDV qui est consacré à des instructions et des discussions de l'équipage avec l'objectif de transformer un groupe d'individus en une équipe efficace.
- *Temps de débriefing* : Une période de temps à la fin de chaque SDV utilisée par les membres de l'équipage pour faire un rapport sur les événements survenus et leurs implications.
- *Membres d'équipage* : Généralement divisés en deux groupes en fonction de leur rôle : les *membres d'équipage du poste de pilotage* sont le pilote (capitaine), copilote, et ingénieur de vol. Le *membres d'équipage de cabine* sont le chef de cabine et les agents de bord.
- *Repos de post-pairing* : Une période de repos entre deux rotations consécutives qui respecte une durée minimale et une durée maximale.
- *Post-pairing* : Une période de repos entre deux rotations consécutives qui contient une journée complète de congé (de minuit à minuit).
- *Routage d'avion* : Une séquence de segments de vols pilotés par un avion spécifique.

## 1.2 Processus de décision en transport aérien

En raison de sa complexité et des perturbations potentielles, la plupart des grandes compagnies aériennes partagent le problème global de décision en deux processus liés : la planification et la mise à jour. Chaque procédure est ensuite divisée en plusieurs étapes qui sont souvent traitées séparément. Le processus de décision des grandes compagnies aériennes est composé de 8 étapes : 5 étapes de planification et 3 étapes de mise à jour. Les 5 étapes de planification sont : la constructions des horaires des vols (*flight scheduling*), l'affectation des avions aux vols (*fleet assignment*), le routage des avions (*aircraft routing*), la construction des rotations d'équipage (*crew pairing*), et l'affectation des blocs mensuels aux membres d'équipage (*crew assignment*). Les 3 étapes de mise à jour des décisions planifiées (en raison de perturbations imprévues) sont : la mise à jour des horaires d'avions (*aircraft recovery*), la mise à jour d'horaire d'équipage (*crew recovery*), et la mise à jour des itinéraires de passagers (*passenger recovery*) (voir la Figure 1.1).

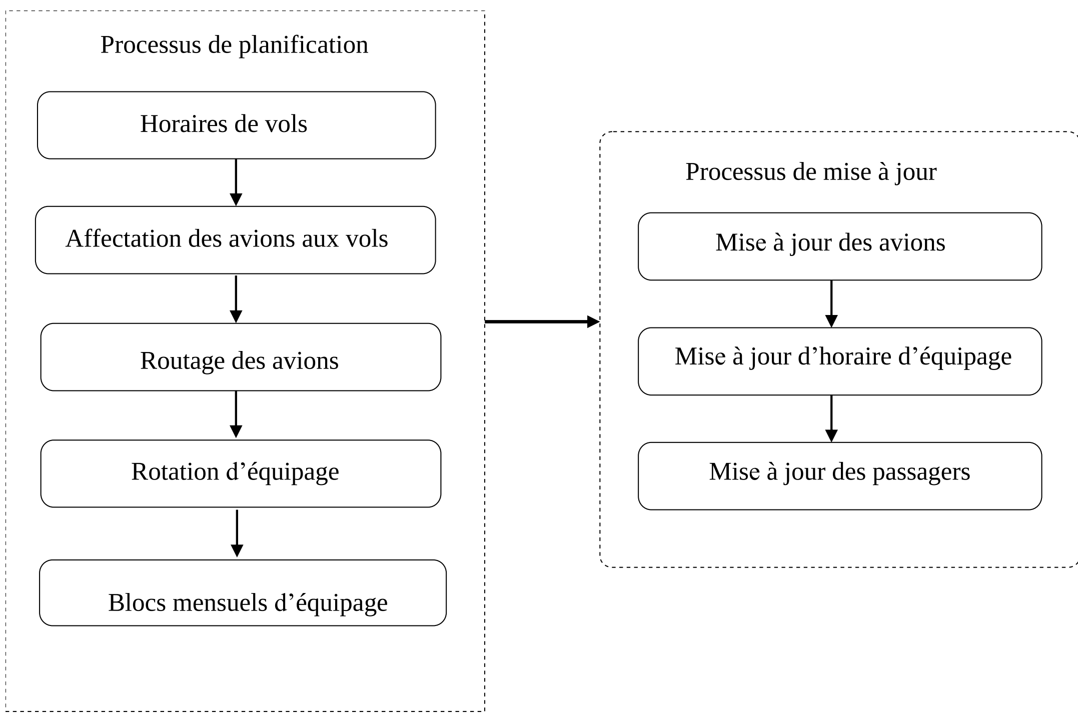


Figure 1.1 Schéma du processus de décision en transport aérien

La première étape de la planification est la construction des horaires de vol dans laquel les vols sont prévus pour un horizon de temps spécifique avec l'objectif de maximiser le bénéfice attendu. La deuxième étape comprend l'affectation des différents types d'avions aux vols, en tenant compte de la demande estimée de passagers de la disponibilité des avions et de la conservation du flot d'avions. Dans la troisième étape le problème de routage d'avion est résolu pour déterminer la séquence des segments de vol couverte par chaque avion tout en satisfaisant les exigences d'entretien. L'étape suivante est la planification des horaires d'équipage. Ce problème est séparable par catégorie d'équipage et par type d'avion (ou de famille d'avions). Il inclut les horaires des équipes qui couvrent tous les vols réguliers et satisfont aux contraintes des conventions collectives. Les *équipages du poste de pilotage* et les *équipages d'agents de bord* sont responsables du service et de la sécurité des passagers. Un membre d'un groupe ne peut normalement pas être remplacé par un membre de l'autre groupe. Les deux groupes sont planifiés séparément pour trois raisons. Tout d'abord, chaque équipage du poste de pilotage est qualifié pour piloter un type d'avion ou une famille, alors que le personnel de cabine peut être affecté à plusieurs types d'avion. Ensuite, le nombre de membres d'équipage de cabine requis dépend du nombre de passagers, alors que la taille de l'équipage du poste de pilotage est fixe. Troisièmement, les équipages du poste de pilotage ont un salaire beaucoup plus élevé que le personnel de cabine en raison de leur niveau d'expertise. En conséquence, la plupart des recherches sur l'optimisation des coûts d'équipage se sont concentrées sur le problème des équipages du poste de pilotage. Ci-après, nous ferons référence aux *membres du poste de pilotage* par la simple mention *membres d'équipage*.

En raison de sa difficulté, traditionnellement, le problème d'horaire d'équipage est traité séquentiellement en deux phases. La quatrième étape est donc la construction des rotations d'équipage suivie par le problème de fabrication des blocs mensuels (la cinquième étape). Le problème de construction des rotations consiste à construire un ensemble de rotations à partir de l'ensemble des segments de vol. Les règles de sécurité et de convention collective portent principalement sur le nombre d'heures maximum de vol par service de vol, sur le temps de repos obligatoire après un certain nombre d'heures de vol ou de services de vol et sur la durée maximale de temps passée à l'extérieur d'une base. L'objectif de cette phase est de trouver un ensemble de rotations qui couvre à un coût minimum l'ensemble des segments de vol. Les coûts incluent le salaire des employés, les frais d'hébergement, le transport, et le repositionnement des membres d'équipage (terrestre ou aérien). Quelquefois, des pénalités sont ajoutées pour réduire l'utilisation des rotations indésirables.

La dernière étape de la planification aérienne est la construction des blocs mensuels pour chaque membre d'équipage en combinant les rotations trouvées précédemment, les repos, et d'autres activités. Chaque bloc mensuel doit commencer et se terminer à la base associée à ce membre. Aussi, chaque bloc mensuel doit satisfaire certaines règles définies par le contrat de travail tel que le nombre maximal de jours de travail consécutifs, le nombre maximal d'heures de travail et le nombre minimal de jours de congé. La façon de construire des blocs mensuels varie d'une compagnie aérienne à une autre, mais en général, on peut les classer en 2 modes :

*Blocs anonymes (Bidline)* : les blocs sont construits de façon anonyme. Les horaires sont construits de manière à couvrir toutes les rotations sans connaître leurs affectations. Ensuite, les employés indiquent leurs préférences d'horaires puis les blocs sont attribués au personnel. Cette procédure est plus fréquente chez les compagnies aériennes nord-américaines.

*Les horaires personnalisés* prennent en compte les tâches préférées des membres de l'équipage et leurs besoins pour des activités spéciales comme les vacances et les périodes de formation. Les rotations sont combinées pour donner les horaires mensuels fournissant un certain niveau de satisfaction de l'équipage. Deux types d'horaires personnalisées sont considérés : *rostering* et *seniority based*. Le *rostering* vise à maximiser la satisfaction globale et peut envisager un deuxième objectif d'équité, mesuré selon des taux de satisfaction des préférences. Les *horaires personnalisés basés sur l'ancienneté* donnent la priorité à la satisfaction des membres d'équipage les plus anciens.

Historiquement, la planification de type bidline a été l'approche la plus utilisée par les compagnies aériennes nord-américaines alors que la planification personnalisée est plus fréquente dans le reste du monde. Cependant, les horaires personnalisés sont de plus en plus utilisés par les compagnies aériennes nord-américaines parce qu'ils offrent des avantages pour les membres d'équipage et les compagnies aériennes. Du point de vue des membres de l'équipage, cette approche considère les demandes des employés lors de la construction des blocs mensuels. Du point de vue de la compagnie, cette approche considère les activités prédéfinies des employés : vacances, formation et rotations au cours du mois précédent. Cela réduit le nombre d'ajustements à apporter à la solution et augmente la productivité.

Une fois que les 5 étapes de planification sont complétées, la compagnie aérienne doit traiter les perturbations apparaissant fréquemment pendant la phase opérationnelle. Les perturbations dans l'exécution du calendrier de la compagnie aérienne peuvent provenir de la météo, de bris d'équipement, de problèmes provenant du personnel. Les perturbations peuvent influencer l'horaire des vols, l'affectation des avions, les activités des équipages et des passagers. Par conséquent, les rotations et les blocs mensuels des membres d'équipage doivent être mis à jour.

La sixième étape du processus de décision correspond à la mise à jour des horaires de vols, à la révision du routage et à l'affectation des avions aux vols. Si nécessaire, certains vols peuvent être retardés ou annulés.

La septième étape est la mise à jour des rotations et des blocs mensuels d'équipage si des vols sont retardés ou annulés. Dans ce cas, il se peut que des vols soient affectés et par conséquent, les membres d'équipage pourraient emprunter des vols différents.

La dernière étape du processus de décision d'une compagnie aérienne consiste à réaffecter les passagers dont l'itinéraire a subi une perturbation en leur affectant des alternatives qui, à partir de leur emplacement se terminent à leur destination ou à un emplacement à proximité.

## 1.3 Problème à l'étude

Dans ce travail de recherche, nous traitons le problème de planification intégrée des rotations et des blocs personnalisés pour les pilotes et les copilotes. Nous optimisons les pilotes et copilotes simultanément, tenant compte de leurs préférences. À notre connaissance, cette recherche est la première à considérer l'optimisation simultanée de la planification des pilotes et des copilotes avec les rotations et les blocs mensuels personnalisés. Contrairement à l'approche séquentielle, l'approche intégrée construit les blocs mensuels directement à partir des vols et non à partir des rotations compte tenu des règles sur les rotations et les blocs mensuels. Elle considère également une fonction du coût globale pour le problème des horaires d'équipage. Prenant les préférences des membres d'équipage en compte, l'algorithme produit des blocs mensuels différents pour les pilotes et copilotes. Afin de préserver la robustesse des blocs mensuels de pilotes et copilotes, nous devons garder des rotations autant similaires entre elles que possible. À notre connaissance, cette étude est la première à examiner l'optimisation simultanée des horaires du poste de pilotage où les rotations et les blocs mensuels personnalisés sont construits par une approche intégrée. Nous résolvons le problème basé sur la génération de colonnes.

Nous considérons quatre objectifs : (1) la minimisation du coût des rotations, (2) la réduction du coût des horaires mensuels, (3) la maximisation de la satisfaction globale des membres de l'équipage, et (4) la maximisation du nombre commun de SDV et de rotations pour pilotes et copilotes. Les objectifs (1), (2) et (3) sont des objectifs évidents. Dans le contexte séquentiel, la solution du problème de rotation ne considère que l'objectif (1). Le problème de construction de blocs mensuels anonymes (bidline) prend en compte l'objectif (2). Le problème de construction de blocs mensuels personnalisés considère les objectifs (2) et (3). Les deux problèmes d'horaires d'équipage anonymes et personnalisés satisfont l'objectif (4) parce que les rotations ne sont pas modifiées quand les blocs mensuels sont construits, et qu'elles sont les mêmes pour les pilotes et les copilotes. La construction des horaires anonymes intégrés considère les objectifs (1) et (2) et satisfait à (4) parce que les horaires sont les mêmes pour les pilotes et copilotes. La construction des horaires personnalisés intégrés prend en compte les objectifs (1), (2) et (3). Toutefois, pour l'objectif (4), il est important de résoudre les problèmes de construction de blocs mensuels des pilotes et des copilotes simultanément, de sorte que les pilotes et copilotes aient des rotations et des SDV similaires lorsque c'est possible.

En réalité, différentes sources de perturbations imprévues telles que des conditions météorologiques défavorables peuvent affecter les horaires planifiés des membres d'équipe. Ces perturbations peuvent causer des vols retardés ou annulés et affecter les horaires des équipes. Sur la base de données fournie par le Bureau of Transportation Statistics (2005-2013), en moyenne 20,39 % des vols réguliers ont été retardés et 1,91 % d'entre eux ont été annulés sur le plan opérationnel. Ces statistiques prouvent que les perturbations sont inévitables. Afin de réduire la propagation des perturbations, le problème de mise à jour doit produire des solutions robustes. Comme autre contribution de cette recherche, nous résolvons le problème de mise à jour des pilotes et des copilotes simultanément pour les horaires mensuels personnalisés.

Il y a cinq différences majeures entre la mise à jour d'horaires d'équipage et leur planification. Premièrement, le problème de mise à jour d'horaires d'équipage ne peut pas être séparé en deux étapes : la construction de rotations et la construction des blocs mensuels. La raison est que les rotations mises à jour doivent s'adapter aux horaires mensuels prévus. En d'autres termes, il s'agit d'une mise à jour pour les blocs mensuels. Deuxièmement, les pilotes et les copilotes doivent être traités simultanément. En fait, les paires de pilote-copilote doivent rester ensemble durant une rotation afin de maintenir la robustesse de la solution. Lorsque les rotations sont différentes entre les pilotes et copilotes, une perturbation de vol dérangera deux rotations, ce qui perturbera plus de vols et se traduira par une propagation de la perturbation. Troisièmement, le problème de mise à jour d'équipages doit être résolu rapidement durant l'opération tandis que le problème de planification de l'équipage peut utiliser plus de temps car il est résolu plusieurs semaines avant le mois de planification. Quatrièmement, le problème de la planification de l'équipage est résolu pour une période de planification (souvent un mois), tandis que la mise à jour des horaires de l'équipage réoptimise les horaires localement (dans une fenêtre de quelques jours) ce qui réduit la dimension du problème d'optimisation. Cinquièmement, les objectifs du problème de planification de l'équipage sont principalement définis en termes de minimisation des coûts tandis que plusieurs objectifs sont en conflit durant la procédure de mise à jour. Un exemple de ces objectifs contradictoires est la minimisation des modifications apportées aux horaires des membres d'équipage et la minimisation du coût d'opération. Parce que le problème de mise à jour doit être résolu rapidement et en temps réel, il doit être de dimension réduite pour être résolu dans un temps raisonnable.

Cependant, le domaine de ce problème de mise à jour doit être suffisamment grand pour permettre de trouver une bonne solution. L'objectif de la mise à jour d'horaires d'équipage est de couvrir l'ensemble des vols donnés d'une manière économique tout en restant le plus près possible des décisions prises dans la procédure de planification. En effect, il faut minimiser la quantité de changements dans les horaires planifiés, ceux entrainés par les changements. En général, l'évolution de la qualité des horaires mis à jour est une tâche difficile. Le processus de mise à jour consiste à appliquer diverses mesures pour réparer les horaires planifiés à un coût minimum tout en minimisant le nombre de vols qui ne peuvent être exploités en raison du manque d'équipage et en utilisant le moins de membres d'équipage de réserve possible.

# CHAPITRE 2 REVUE DE LITTÉRATURE

Le problème de planification des horaires d'équipage est généralement séparé en deux étapes qui sont résolues séquentiellement. La première consiste à construire les rotations d'équipage et la seconde consiste à construire les blocs mensuels. Récemment, des chercheurs ont développé des approches d'optimisation intégrée pour la construction des horaires d'équipage. La Section 2.1 présente une revue de littérature sur le problème de planification séquentielle d'équipage. La Section 2.2 présente les modèles et les algorithmes pour le problème de la planification intégrée d'équipage.

Les problèmes de construction de rotations et de blocs mensuels d'équipage sont généralement formulés comme un problème de partitionnement d'ensemble, *set partitioning problem (SPP)*, ou un problème de recouvrement, *set covering problem (SCP)*, avec des contraintes supplémentaires. Les problèmes sont difficiles à résoudre en raison du nombre de contraintes et de variables. Depuis 1960, plusieurs méthodes de plans coupants et d'énumération implicite (*branch-and-bound*) ont été développées pour résoudre ce type de problème. Les quatre méthodes de résolutions les plus courantes sont la relaxation lagrangienne (Geoffrion (1974), Fisher (1981), Fisher (1985), et Martin (1999)), la méthode de génération de colonnes (Desaulniers et al. (1998), Desrosiers et al. (1995), et Barnhart et al. (1996)), la méthode d'agrégation des contraintes (Elhallaoui et al. (2005)), et la décomposition de Benders (Benders (1962) et Minoux (1986)). Depuis les années 1990, l'approche dominante est basée sur la formulation d'un SCP résolue par génération de colonnes (voir Desrosiers et Lübbecke (2005), Desrosiers et al. (1995), et Barnhart et al. (1996)).

Barnhart et al. (2003) offrent une excellente revue de littérature ainsi qu'un article de synthèse sur les problèmes de construction des rotations d'équipage. Gopalakrishnan et Johnson (2005) proposent un article de synthèse sur les différentes approches et méthodologies de résolution pour les problèmes de planification d'horaire d'équipage. Desaulniers et al. (2005) passent en revue les modèles et les algorithmes pour résoudre des problèmes de grande taille reliés au transport aérien. Plus récemment, des chercheurs ont exploré le problème de construction des rotations mensuelles, le problème de construction des blocs mensuels personnalisés, et la planification intégrée d'équipage.

## 2.1 Planification séquentielle de l'équipage

La Section 2.1.1 présente une revue de littérature pour le problème de rotation d'équipage et la Section 2.1.2 présente une revue de littérature pour le problème d'affectation des blocs mensuels.

### 2.1.1 Problème de rotation d'équipage

Pour chaque catégorie d'équipage et chaque type de flotte d'avions, le problème de construction de rotations d'équipage trouve un ensemble de rotations à coût minimal afin que chaque vol prévu soit réalisé par un équipage. La méthodologie de résolution du problème dépend de la taille, de la structure du réseau de la compagnie aérienne (par exemple, *hub-and-spoke*), des règles, des conventions collectives et de la structure des coûts. Trois horizons temporels sont généralement étudiés : un horizon quotidien, hebdomadaire et mensuel. Le problème *quotidien* suppose que les vols sont identiques (ou assez semblables) pour tous les jours de l'horizon de planification et que les rotations de coût minimal sont générées pour les vols prévus pour une journée. On produit une solution cyclique ; c'est-à-dire que le nombre d'équipages présents dans chaque ville le soir est le même que le matin. Ainsi on peut produire des solutions hebdomadaires et mensuelles en juxtaposant la solution journalière. Quand les horaires de vols ne sont pas tout à fait identiques tous les jours, on supprime les solutions de la journée type les jours où elles ne s'appliquent pas et on réoptimise pour créer de nouvelles rotations couvrant les vols qui ne le sont pas. Le problème *hebdomadaire* suppose que les vols sont identiques (ou assez semblables) chaque semaine, et le problème de rotation est résolu pour les vols prévus pour une semaine type. Le problème *mensuel* traite globalement un mois complet. Des recherches récentes ont porté sur les problèmes hebdomadaires et mensuels. En raison de la période des vacances et des variations dans les horaires de vol, l'horizon de temps mensuel est le plus réaliste.

Le problème de rotation d'équipage est généralement formulé comme un SPP ou un SCP ayant une contrainte de partitionnement/ou de recouvrement associé à chaque tâche (vol) ainsi qu'une variable associée à chaque rotation réalisable. Il y a généralement des contraintes supplémentaires correspondant aux règles de sécurité et aux règlements tel que le temps de vol maximal pour chaque base aérienne. Puisqu'il y a souvent un nombre élevé de rotations réalisables, le problème est généralement résolu en deux étapes dans les travaux les plus anciens : la première étape génère un sous-ensemble de bonnes rotations par énumération, et la seconde résout le SPP afin de sélectionner la meilleure combinaison de rotations dans ce sous-ensemble. Plusieurs algorithmes heuristiques de recherche locale ont été proposés. Un exemple typique est présenté par Marsten et Shepardson (1981). Ils proposent un modèle de SPP et une technique de résolution basée sur la relaxation lagrangienne et l'optimisation avec la méthode de sous-gradient. Ils rapportent des essais sur des ensembles de données de Flying Tiger Line, Pacific Southwest Airlines, Continental Airlines et Helsinki City Transport. Gershkoff (1989) propose un algorithme heuristique d'amélioration de la solution. À chaque itération, il sélectionne un sous-ensemble de vols pour lesquels il génère des rotations réalisables et résout le SPP afin de choisir les rotations de coût minimal qui couvriront les vols sélectionnés. Les résultats sont présentés pour des vols d'American Airlines. Anbil et al. (1991) ont implanté cet algorithme dans les logiciels d'American Airlines et expliquent les améliorations permettant de résoudre des problèmes plus compliqués.

Anbil et al. (1992) proposent une approche globale dans une étude conjointe avec IBM et American Airlines Decision Technologies. Des millions de rotations possibles (colonnes) sont énumérées à priori et plusieurs milliers sont fournies au solveur de la relaxation linéaire du problème à chaque itération. Après l'optimisation, la plupart des colonnes hors base sont éliminées et de nouvelles colonnes sont ajoutées. Le processus se poursuit jusqu'à ce que toutes les colonnes aient été prises en compte. Bixby et al. (1992) proposent un algorithme basé sur la méthode de point intérieur et sur l'algorithme du simplexe afin de résoudre la relaxation linéaire pour des problèmes de grande taille. Leurs résultats montrent que l'approche hybride est plus efficace. Hoffman et Padberg (1993) proposent de résoudre le SPP avec un algorithme d'énumération implicite et l'ajout de plans coupants. Ils présentent des résultats pour 68 ensembles de données provenant de quatre compagnies aériennes. Les sauts d'intégrité sont grands (jusqu'à 5 %). Klabjan et al. (2001) améliorent l'approche de Hoffman et Padberg. Leur algorithme énumère des millions de rotations aléatoires. Puis, la relaxation linéaire est résolue et des millions de colonnes sont sélectionnées en fonction de leurs coûts réduits. Le nombre est ensuite réduit par une méthode heuristique basée sur la relaxation linéaire et une solution entière est trouvée en utilisant un solveur commercial de programmation en nombres entiers. Le branchement combine le *strong branching* avec une règle de branchement spécialisée. Des résultats numériques sont rapportés pour une grande compagnie aérienne américaine.

Les algorithmes heuristiques ont trois principales lacunes. Premièrement, ils ne considèrent pas tous les vols prévus simultanément, et doivent exécuter de nombreuses itérations avant de trouver une solution de bonne qualité. Deuxièmement, ils ne considèrent pas toutes les rotations réalisables. Troisièmement, le saut d'optimalité est grand et on peut être loin d'une solution optimale. Par conséquent, des approches plus sophistiquées ont été proposées. Lavoie et al. (1988) introduisent la génération de colonnes pour ce problème. Ils résolvent un SCP avec un algorithme du simplexe et génèrent des colonnes en résolvant un problème de plus court chemin. Ils obtiennent des résultats de bonne qualité et des sauts d'intégrité beaucoup plus petits. Plusieurs algorithmes de génération de colonnes (voir Desrosiers et al. (1991), Barnhart et al. (1994), Desaulniers et al. (1997), et Desaulniers et al. (1998)) ont été proposés et considèrent l'ensemble des rotations réalisables.

Wedelin (1995) introduit un nouvel algorithme d'approximation pour la résolution en nombres entiers des problèmes binaires de grande taille. Le schéma d'approximation ajuste les coûts le moins possible, de sorte que la relaxation linéaire du nouveau problème ait une solution entière. L'algorithme a été appliqué à des ensembles de données de grande taille extraits du système Carmen (le modèle est le SCP). Les résultats montrent que l'algorithme se compare favorablement avec CPLEX en termes de temps de calcul et de qualité de la solution. Andersson et al. (1998) présentent une synthèse du système de construction de rotations utilisé dans plusieurs grandes compagnies aériennes européennes. Ce système est efficace, car il intègre des approches manuelles et automatiques à la planification, il est facile à utiliser et il donne des solutions robustes et de bonne qualité.

Vance et al. (1997) proposent un modèle en deux étapes afin de résoudre le problème de planification des équipages. La première étape permet de choisir un ensemble de services de vols qui couvrent les vols prévus. La deuxième étape construit alors les rotations basées sur ces services de vols en utilisant un algorithme basé sur la génération de colonnes. Des résultats sont présentés pour une compagnie aérienne américaine majeure. La nouvelle méthodologie trouve des meilleures bornes inférieures, mais demande plus de temps de calcul. Barnhart et Shenoi (1998) résolvent un modèle approximatif du problème de rotation d'équipage et utilisent cette solution comme la solution initiale pour les approches conventionnelles. Des résultats sont présentés pour une compagnie aérienne de long-courriers. Hu et Johnson (1999) proposent un algorithme du simplexe avec sous-problème primal-dual afin d'accélérer la résolution de la relaxation linéaire. Des résultats numériques sont présentés pour les instances avec un maximum de 930 vols.

Hjorring et Hansen (1999) proposent un algorithme de boîte noire pour simplifier la mise en œuvre des différentes réglementations. Ils intègrent la méthode de génération de colonnes avec un sous-problème de génération de rotations, basé sur un réseau de services de vols et un algorithme de $k^{ème}$ plus court chemin. Subramanian et Sherali (2008) proposent un système d'optimisation de *effective deflected subgradient optimisation* pour générer de bonnes solutions duales pour les problèmes de relaxation linéaire. Cette approche, utilisée conjointement avec la méthode de génération de colonnes, est intégrée dans l'optimiseur de rotations d'équipage à United Airlines. Les tests utilisant des ensembles de données historiques montrent que des bénéfices significatifs peuvent être obtenus en utilisant cette approche au lieu d'un solveur standard pour les programmes linéaires intermédiaires. AhmadBeygi et al. (2009) considèrent une nouvelle approche de programmation en nombres entiers qui est simple à mettre en œuvre, ce qui facilite le prototypage et les essais de nouvelles idées. Le modèle qu'ils proposent utilise des variables de connexion et des variables du marché (market variables) pour capturer la fonction de coût et les contraintes non linéaires. Les résultats présentés pour les ensembles de données provenant d'un grand transporteur américain dont le réseau est de type *hub-and-spoke* démontrent la performance de l'approche. Dück et al. (2011) présentent un algorithme de génération de colonnes avec l'ajout de coupes. L'objectif est de minimiser le nombre de rotations pour couvrir un ensemble de vols prévus en tenant en compte de la réglementation, mais en ignorant les contraintes de durée de service. Le problème est formulé comme un problème de partitionnement avec contraintes de ressources. Cet algorithme a été appliqué à certaines petites et moyennes instances d'une compagnie aérienne européenne. Saddoune et al. (2013) introduisent une approche en horizon fuyant pour trouver les rotations de coût minimum pour la formulation de partitionnement du problème de rotation. Ils discutent des faiblesses de l'approche traditionnelle dans laquelle les problèmes quotidiens, hebdomadaires, et mensuels sont résolus de façon séquentielle. Des résultats numériques pour une importante compagnie américaine de courts et moyens courriers donnent de bons résultats.

### 2.1.2 Blocs mensuels d'équipage

Il y a plusieurs fonctions d'objectifs possibles pour le problème de fabrication des blocs mensuels (problème d'affectation d'équipage). Comparée au problème de rotations d'équipage, la fabrication de blocs mensuels d'équipage a reçu moins d'attention par le passé.

Dans le contexte du problème de fabrication des blocs mensuels anonymes (*bidline*), Beasley et Cao (1996) présentent une formulation de programmation en nombres entiers ; ils utilisent la relaxation lagrangienne et l'optimisation par sous-gradient. Cette approche s'insère dans un schéma d'énumération implicite pour trouver la solution optimale. Des résultats sont fournis pour les cas de tests générés aléatoirement avec un maximum de 204 membres d'équipage et 500 tâches. Campbell et al. (1997) décrivent un système de génération de blocs mensuels anonymes pour une compagnie américaine de transport de marchandises (FedEx). L'objectif est de minimiser le nombre de *bidlines* et de minimiser le temps de vol non effectué à ces bidlines. Ils utilisent un algorithme métaheuristique basé sur le recuit simulé. Jarrah et Diamond (1997) proposent une approche heuristique fondée sur les SPP pour le problème de *bidline* utilisant la méthode de génération de colonnes à priori. L'objectif est de maximiser le temps de crédit couvert tout en minimisant le nombre de *bidlines*. Le système est semi-automatique : l'utilisateur peut influencer le sous-ensemble de colonnes générées. Ce système est mis en œuvre dans une grande compagnie aérienne américaine, et de bons résultats sont obtenus. Christou et al. (1999) introduisent une approche en deux phases basée sur des algorithmes génétiques pour la construction de bidline chez Delta Air Lines. L'objectif est de maximiser la valeur totale moyenne et la qualité des *bidlines*. La première phase de l'algorithme a pour but de construire de bonnes *bidlines*, alors que la deuxième phase se termine par la construction d'une affectation valide des *bidlines*, en tenant compte des rotations non couvertes lors de la première phase. Les résultats, pour un maximum de 320 membres d'équipage, montrent que l'algorithme fournit d'importantes économies par rapport à l'approche semi-automatisée pour la construction de *bidlines* utilisée chez Delta Air Lines.

Weir et Johnson (2004) proposent une approche en trois phases pour la génération de bidlines. Dans la première phase, un problème mixte en nombres entiers est résolu pour fournir des *bidlines* tentatives (*patterns*). La deuxième phase, basée sur un SPP, utilise ces bidlines pour déterminer des listes finales de blocs mensuels qui couvrent toutes les rotations. Si la deuxième phase échoue, une troisième phase intègre alors les rotations non couvertes dans les blocs mensuels. De bons résultats pour un maximum de 150 membres d'équipage sont présentés. K. et al. (2010) décrivent deux algorithmes heuristiques pour résoudre le problème de fabrication de bidline basé sur un SPP. Autant que possible, chaque bidline devrait avoir le même nombre de jours de congé et le même nombre d'heures rémunérées (bidline de l'équité). La première heuristique est un algorithme de *branch-and-price* standard qui s'appuie sur une procédure d'arrondi pour obtenir des solutions entières. Le deuxième algorithme combine l'agrégation dynamique de contraintes (Elhallaoui et al., 2005) avec la première heuristique. Les résultats montrent que pour les plus grandes instances (jusqu'à 564 pilotes et 2924 rotations), l'heuristique d'agrégation dynamique de contraintes donne de meilleures solutions que l'heuristique standard de *branch-and-price*.

Pour le problème des blocs personnalisés (*rostering*), Day et Ryan (1997) considèrent les opérations court-courriers d'Air New Zealand. Dans leur approche utilisant la programmation en nombres entiers, les jours de congé sont d'abord attribués puis les rotations et les autres activités sont affectées. La méthode conduit à la construction efficace de blocs mensuels de bonne qualité puisque la plupart des rotations ne durent qu'une journée, et il est utilisé depuis 1993 pour tous les court-courriers agents de bord d'Air New Zealand. Gamache et al. (1999) décrivent un SPP généralisé et une approche heuristique basée sur la génération de colonnes pour trouver de bonnes solutions entières pour le problème de construction de blocs mensuels personnalisés, maximisant la satisfaction et tenant compte des activités pré-attribuées. Ils utilisent des stratégies de contrôle dans la génération de colonnes pour réduire le temps de calcul pour les grands problèmes. Les résultats présentés pour les instances de taille moyenne d'Air France démontrent les bonnes performances de l'algorithme, tant en termes de qualité des solutions obtenues qu'en termes de temps d'exécution. Les stratégies d'accélération permettent de réduire le temps de calcul d'un facteur de plus de 1000. Les blocs obtenus sont comparés avec les blocs construits par le programme de CADET (alors en usage chez Air France), et les nouveaux blocs laissent moins de tâches non couvertes. El Moudani et al. (2001) proposent une approche bi-critère heuristique qui prend en compte la satisfaction des membres d'équipage. Cette approche est combinée à un algorithme génétique pour produire des blocs mensuels moins coûteux qui permettent d'atteindre un niveau spécifique de la satisfaction de l'équipage. Les résultats obtenus pour les données d'une compagnie aérienne moyen-courrier sont donnés. König et Strauss (2000a,b) introduisent une heuristique qui énumère implicitement les blocs en utilisant des techniques de propagation. Cette approche est mise en œuvre dans l'algorithme de SWIFTROSTER, et de bons résultats sont obtenus pour les grandes compagnies aériennes européennes de moyenne et grande taille. Fahle et al. (2002), Kohl and Karisch (2000) et Sellmann et al. (2002) décrivent le projet Parrot (1997), qui est basé sur la génération de colonnes et la programmation par contraintes. Le problème maître (la sélection des blocs) est résolu comme un programme linéaire, et la programmation par contraintes est utilisée pour générer les blocs. Kohl and Karisch (2004) fournissent une étude complète du système de *rostering* de Carmen utilisé chez KLM depuis 1995. Ils mettent en évidence des considérations pratiques relatives aux paramètres de production de systèmes de planification d'équipages. Maenhout et Vanhoucke (2010) utilisent la décomposition de Dantzig–Wolfe et proposent un algorithme métaheuristique de recherche de dispersion pour attribuer des listes personnalisées à chaque membre de l'équipage tout en optimisant le coût total des opérations et la qualité des blocs. Ils comparent leur approche avec une méthode exacte basée sur la *branch-and-price* et sur la recherche à voisinage variable par plus grande pente (*steepest-descent variable neighborhood search*). Des résultats sont donnés pour des instances avec un maximum de 150 pilotes et 800 rotations.

Pour le problème de fabrication des blocs personnalisés avec séniorité (*preferrential bidding*), Gamache et al. (1998) étudient ce problème pour les pilotes chez Air Canada. Les pilotes peuvent exprimer leurs préférences sur plus de 75 facteurs (*bids*) ; par exemple les choix de jours de congé ou les choix de vols. Chaque employé associe un poids à chaque facteur et ces poids sont utilisés pour calculer des scores pour les blocs potentiels. Un problème *résiduel* est alors résolu pour chaque employé, du plus ancien au plus jeune pour maximiser sa satisfaction tout en assurant que le problème reste réalisable pour les suivants. Les problèmes sont modélisés comme des programmes linéaires en nombres entiers et sont résolus par génération de colonnes intégrées dans un arbre de *branch-and-bound*. Des résultats sont présentés sur 24 jeux de données d'Air Canada. Cette recherche a abouti à un preferential bidding system (PBS) utilisé chez Air Canada depuis 1995. Achour et al. (2007) introduisent la première méthode de résolution exacte basée sur la génération de colonnes pour le PBS. Ils résolvent la séquence de programmes linéaires selon l'ordre d'ancienneté, et le bloc d'un employé est fixé s'il est le seul bloc optimal. Si la solution n'est pas unique, on ajoute une contrainte pour choisir parmi les solutions pendant que l'on optimise les blocs des suivants. Les résultats présentés pour les jeux de données réelles concernent jusqu'à 91 pilotes et indiquent une amélioration substantielle de la qualité des solutions.

## 2.2 Planification intégrée d'équipage

Comme expliqué précédemment, résoudre le problème de la planification de la compagnie aérienne par l'approche séquentielle ne garantit pas un résultat optimal pour le problème de la planification globale. Récemment, des chercheurs ont étudié l'intégration de certaines étapes du problème de planification. Une revue de la recherche sur l'intégration de la construction des rotations d'équipage avec le routage des avions et/ou l'affectation des avions aux vols est présentée à la Section 2.2.1. La Section 2.2.2 présente une revue sur la recherche sur l'intégration des horaires de vols et d'affectation des avions aux vols. La Section 2.2.3 présente la recherche sur l'intégration du routage des avions et la construction des rotations d'équipage. L'intégration de l'affectation des avions aux vols et des rotations d'équipage est présentée à la Section 2.2.4. Finalement, la Section 2.2.5 discute la recherche sur l'intégration des rotations d'équipage et des blocs mensuels.

### 2.2.1 Intégration des problèmes de rotations d'équipage, des routages des avions, et de l'affectation des avions aux vols

Cordeau et al. (2001), Cohn and Barnhart (2003), Mercier et al. (2005), et Chen et al. (2012) abordent le problème de l'intégration du routage d'avion et de rotations d'équipage. Sandhu et Klabjan (2007) et Gao et al. (2009) considèrent l'intégration de l'affectation des avions aux vols et des rotations d'équipage. Klabjan et al. (2002) considèrent l'intégration d'horaire de vols, du routage d'avion, et des rotations d'équipage. Mercier et Soumis (2007) intègrent le routage des avions avec des horaires flexibles et les horaires d'équipage. Papadakos (2009) propose différents modèles d'intégration de l'affectation des avions et de leurs routages en tenant compte de l'entretien et des rotations d'équipage. Ruther (2010) étudie l'intégration du routage d'avion et des rotations d'équipage.

### 2.2.2 Intégration des horaires de vols et d'affectation des avions aux vols

Lohatepanont et Barnhart (2004) introduisent des modèles et des algorithmes heuristiques. Ils présentent des expérimentations sur des données de taille moyenne d'une compagnie aérienne américaine majeure. Sherali et al. (2010) proposent une approche de décomposition de Benders ; ils considèrent des horaires de vol flexibles, des préoccupations d'équilibre horaire, et reprennent les questions en compte (recapture issues into account). Ils fournissent des résultats numériques pour des petits ensembles de données de United Airlines.

### 2.2.3 Intégration du routage des avions et des rotations d'équipage

Cordeau et al. (2001) proposent un algorithme basé sur la décomposition de Benders et la génération de colonnes. De bons résultats sont présentés sur un horizon de trois jours. Cohn et Barnhart (2003) introduisent une heuristique et des algorithmes optimaux ; ils effectuent des expériences sur deux petites instances. Mercier et al. (2005) présentent deux approches de décomposition de Benders : l'une pour laquelle le routage des avions est dans le problème maître, et l'autre pour laquelle les rotations d'équipage sont considérées. Leurs expériences sur des données provenant de deux grandes compagnies aériennes donnent de meilleures solutions avec les équipages dans le problème maître. Weide et al. (2010) introduisent une procédure itérative qui alterne entre les problèmes d'avions et d'équipages. Cette procédure tente de créer des solutions robustes en réduisant le nombre de membres d'équipage et de changements d'avion.

### 2.2.4 Intégration de l'affectation des avions aux vols et des rotations d'équipage

Sandhu et Klabjan (2007) présentent un modèle intégrant l'affectation des avions aux vols avec les rotations d'équipage. Ils négligent les contraintes d'entretien d'avions. Ils présentent deux algorithmes : 1) la relaxation lagrangienne combinée avec la génération de colonnes et 2) la décomposition de Benders. Les résultats sont fournis pour des petites instances. Gao et al. (2009) présentent un modèle et l'algorithme robuste intégré de la planification de la flotte et de l'équipage. Leurs résultats numériques donnent de bons résultats pour les données d'une grande compagnie aérienne américaine.

Klabjan et al. (2002) développent un modèle et un algorithme pour l'intégration des horaires de vol, de routage d'avions, et des rotations d'équipage. Ils présentent de bons résultats pour de petites instances. Pour le même problème, Papadakos (2009) introduit un modèle de recouvrement qui résout par la décomposition Benders améliorée combinée à une génération de colonnes. Il rapporte de bons résultats pour de petits ensembles de données. Cacchiani et

Salazar-González (2013) proposent une heuristique et un algorithme basé sur la génération de colonnes. Ils présentent des résultats pour de petites instances sans vols de nuit.

### 2.2.5 Intégration des problèmes de rotations et de blocs mensuels

L'intégration des rotations d'équipage et de blocs mensuels est étudiée par Zeghal et Minoux (2006), Guo et al. (2006), Souai et Teghem (2009), Deng et Lin (2011), Saddoune et al. (2012), Saddoune et al. (2011) et Azadeh et al. (2013).

Zeghal et Minoux (2006) sont les premiers à avoir abordé l'intégration de la construction des rotations avec la fabrication des blocs mensuels des pilotes, des premiers officiers et des instructeurs (un instructeur est un pilote qui, au besoin, peut remplacer un officier). Ils proposent un modèle de programmation linéaire en nombres entiers utilisant des contraintes de clique pour l'intégration des rotations et l'affectation de blocs mensuels d'équipage. Ils supposent que les services des vols peuvent être générés a priori, et des mises en place (deadhead) peuvent être introduites si nécessaire, sans coût supplémentaire. Pour améliorer l'efficacité des méthodes exactes, une méthode heuristique basée sur une stratégie d'arrondi est inscrite dans une procédure d'exploration partielle d'un arbre de branchement. Ils résolvent le problème avec deux algorithmes de *branch-and-bound*, un exact et une heuristique, et présentent de bons résultats pour de petites instances de Tunisair sur un horizon de cinq jours (avec un maximum de 101 vols et 40 membres d'équipage) et un horizon d'un mois (jusqu'à 195 vols et 18 membres d'équipage). Guo et al. (2006) introduisent un algorithme heuristique pour intégrer partiellement les problèmes de rotations d'équipage et de blocs mensuels. Il est basé sur les réseaux d'espace-temps agrégés où les membres d'équipage sont inégalement répartis parmi les bases, et où leur disponibilité change dynamiquement au cours de la période de planification. L'algorithme génère un premier groupe de rotations qui sont séparées par des repos hebdomadaires. Certaines parties de ces rotations sont alors réarrangées dans des calendriers d'équipage individuels. Des tests sont effectués sur un horizon de 15 jours (avec un maximum de 1977 vols et 188 membres d'équipage) et un horizon de 31 jours (avec 808 vols et 44 membres d'équipage). Souai et Teghem (2009) proposent un algorithme génétique hybride pour intégrer le problème de rotations d'équipage et de blocs d'équipages. Ils utilisent trois heuristiques pour faire face aux règlements. Ils fournissent des résultats pour trois petites instances et un horizon de planification mensuel (avec un maximum de 1 872 vols et 68 pilotes).

Deng et Lin (2011) utilisent un algorithme d'optimisation avec une colonie de fourmis pour résoudre le problème des horaires d'équipage. Ils formulent le problème comme un problème de voyageur de commerce sur un graphe pondéré et contraint (*weighted and constrained graph*).

Les résultats pour de petites instances réelles indiquent que de bonnes solutions peuvent être trouvées. Saddoune et al. (2012) développent un modèle et un algorithme basé sur la génération de colonnes et l'agrégation dynamique de contraintes de Elhallaoui et al. (2005) pour l'intégration du problème de rotations et de blocs mensuels dans le cas non personnalisé. Ils rapportent de bons résultats pour sept ensembles de données d'une compagnie aérienne nord-américaine. Le plus grand a 7765 vols prévus et 305 pilotes. Ils obtiennent une réduction moyenne du coût de 3,37 %, mais le temps de calcul est de 6,8 fois supérieur à celui de l'approche séquentielle de construction des horaires d'équipage. Saddoune et al. (2011) réduisent le temps de calcul de l'algorithme de Saddoune et al. (2012). Ils introduisent une méthode d'agrégation bi-dynamique de contraintes qui utilise la structure de voisinage lors de la génération de colonnes. Les temps de calcul sont réduits d'un facteur moyen de 2,3 et le coût de la solution est réduit de 4,02 % à 4,76 %. Azadeh et al. (2013) introduisent une méta-heuristique hybride pour l'optimisation non-linéaire d'un problème d'horaires d'équipage dont l'objectif est de minimiser le coût total de l'équipage tout en respectant les règlements. Ils proposent également deux algorithmes hybrides basés sur un algorithme génétique et de l'optimisation avec colonie de fourmis. Ils réalisent des expériences sur 20 jeux de données générés aléatoirement.

## 2.3 Problème de mise à jour d'horaires d'équipages aériens

En raison de la nature du problème de la mise à jour des opérations aériennes, il est nécessaire que le temps de calcul soit court. Par conséquent, la taille du problème d'optimisation doit être largement réduite. Cette réduction peut être obtenue en considérant un plus petit nombre de membres d'équipage dans le problème de mise à jour ou en restreignant la durée de la fenêtre de mise à jour.

À notre connaissance, la première étude sur la mise à jour des opérations aériennes est fournie par Clarke (1998). Il donne une étude synthèse d'opérations aériennes et des causes d'irrégularités. Il présente également des systèmes d'aide à la décision et des approches de résolution, en utilisant des données opérationnelles sur le marché domestique américain. Filar et al. (2001) et Kohl et al. (2007) font une revue des travaux antérieurs sur les procédures de décision pour les problèmes de mise à jour en transport aérien. Ils rendent compte de leurs expériences de recherche et développement en gestion de la perturbation du transport aérien à grande échelle. Une autre synthèse sur les différents aspects de la gestion des perturbations dans l'industrie du transport aérien est fournie par Clausen et al. (2010). De plus, ils conduisent une étude comparative entre les problèmes de planification et la mise à jour d'avions/d'équipage. Plus récemment, Barnhart and Smith (2012) donne un aperçu sur le rôle de la recherche opérationnelle dans l'amélioration de l'efficacité de la compagnie aérienne au niveau opérationnel.

La recherche sur la mise à jour des opérations aériennes a tout d'abord commencée par l'étude des horaires d'avions qui font face à des opérations irrégulières (Clausen et al. (2010)). Ceci est peut-être dû à la nature moins complexe de ce problème par rapport à la mise à jour des horaires d'équipage (i.e. le nombre d'avions est moins important que le nombre de membres d'équipage). De plus, les règles d'opérations des avions sont moins compliquées que les règles de construction d'horaires d'équipage. Teodorovic et Guberinic (1984), Teodorovic et Stojkovic (1990), Jarrah et al. (1993), Rakshit et al. (1996), Mathaisel (1996), Talluri (1996), Yan and Yang (1996), Clarke (1997), Clarke and Laporte (1997), Yan and Tu (1997), Cao and Kanafani (1997a), Cao and Kanafani (1997b), Luo and Yu (1997), Argüello et al. (1997), Luo and Yu (1998), Thengvall et al. (2000), Thengvall et al. (2001), Thengvall et al. (2003), Bard et al. (2001), Rosenberger et al. (2003), Andersson and Värbrand (2004), Andersson (2006), Liu et al. (2008), Eggenberg et al. (2007), et Zhao and Zhu (2007) ont étudié le problème de mise à jour de l'opération des avions. Nous ne nous concentrons pas sur l'examen de la littérature de mise à jour des horaires des avions, parce que ce problème n'est pas l'objet de notre recherche.

Dans le contexte de la mise à jour d'équipage, trois hypothèses générales ont été considérées. La première suppose que les horaires des vols sont déjà réparés quand le problème de mise à jour des horaires d'équipage est résolu ; c'est-à-dire que, les horaires de vol sont considérés comme des données d'entrée pour le problème de mise à jour d'équipage. Dans ce cas, Wei et al. (1997) et Song et al. (1998) fournissent une formulation de couverture d'ensembles généralisée pour le problème de mise à jour des rotations d'équipage avec des membres en réserve. L'objectif est de réparer les rotations perturbées dès que possible, tout tenant en compte de la réduction des coûts opérationnels. L'algorithme heuristique de *branch-and-bound* donne des résultats de bonne qualité pour des instances de petite taille. Stojković et al. (1998) proposent une formulation de partitionnement d'ensembles pour le problème d'affectation des équipages et utilisent la génération de colonnes comme méthode de résolution. L'objectif est de couvrir, à coût minimal, tous les vols grâce aux candidats d'équipages disponibles. Ils permettent seulement la modification d'une rotation par membre d'équipage. Afin de trouver des rotations modifiées pour les membres d'équipage sélectionnés, ils résolvent simultanément le problème de rotation d'équipage classique et les problèmes d'affectation mensuels personnalisés. Ils rapportent des résultats numériques pour des petites instances (avec un maximum de 32 membres d'équipes et 210 vols) pour une journée ou sept jours de périodes opérationnelles. Medard and Sawhney (2007) élargissent le cadre de mise à jour de Stojković et al. (1998) en autorisant le changement de plus d'une rotation pour chacun des membres d'équipage. Ils proposent une approche intégrant le problème de mise à jour des rotations et des blocs mensuels. Ils résolvent le problème de mise à jour par génération de colonnes et fournissent des résultats pour de petites et moyennes instances. Nissen and Haase (2006) présentent une approche de mise à jour traitant un service de vol par pilote pour une compagnie européenne. Il utilise une formulation de couverture d'ensembles et une méthode de résolution basée sur le *branch-and-price*. Guo (2005) propose une formulation de partitionnement d'ensemble pour le problème de mise à jour d'équipage avec comme objectif la minimisation du nombre de modifications des blocs mensuels planifiées. Sa méthode de résolution est une combinaison de la génération de colonnes et d'un algorithme génétique, permettant d'obtenir une amélioration dans la qualité et le temps de calcul.

Dans la deuxième hypothèse, les annulations de vols sont autorisées. Johnson et al. (1994) présentent une formulation de couverture d'ensembles dont l'objectif tient compte de la construction des rotations et les coûts de mise en place (deadhead) tout en forçant les membres de l'équipage à rester à la base à laquelle ils étaient déjà associés. Des résultats sont présentés pour de petites instances. Lettovsky et al. (2000) présentent une formulation de couverture d'ensemble pour le problème de mise à jour de l'équipage. Ils utilisent un générateur rapide de rotations et une technique de *branch-and-price* et choisissent la meilleure parmi les rotations d'équipage générées pour un petit nombre de perturbations. La méthode de génération de rotations est conçue pour minimiser les modifications apportées aux blocs mensuels initiaux. Yu et al. (2003) discutent de la mise en œuvre d'un système de soutien à la décision pour la mise à jour des horaires d'équipage à Continental Airlines, qui est une version améliorée du modèle de Wei (1997). Ils rendent compte de résultats de bonne qualité et des temps de résolution raisonnables de solutions pour les petites et moyennes instances.

La troisième hypothèse considère la procédure de mise à jour d'équipage lorsque l'on permet de retarder le départ des vols. Stojković and Soumis (2001) étendent le travail de Stojković et al. (1998) lorsque des retards sont intégrés dans le problème de mise à jour de l'équipage. Ils présentent un modèle de couverture d'ensemble qu'ils résolvent par génération de colonnes. L'ajout de membres d'équipage de réserve est également autorisé. Ils présentent des résultats pour des instances avec un maximum de 59 pilotes et 52 vols retardés sur 190 vols. Stojković and Soumis (2005) étendent le travail de Stojković and Soumis (2001) et présentent une optimisation simultanée de la modification des heures de départ et des services de vols individuels prévus pour plusieurs membres de l'équipage. L'objectif est de couvrir un nombre maximum de vols sur une journée d'opération et de minimiser les modifications à la fois dans le calendrier de vol et dans l'impact sur le lendemain pour l'ensemble des membres de l'équipage. Des résultats numériques pour des instances de taille moyenne sont rapportés. Abdelghany et al. (2004) fournissent un système d'aide à la décision de mise à jour de l'équipage lorsque les retards de vols sont autorisés pour les compagnies aériennes commerciales de type *hub-and-spoke*. Ils présentent des résultats de bonne qualité pour des instances de taille moyenne.

Depuis 1997, la communauté s'intéresse aussi à l'intégration des différentes étapes du problème de mise à jour dans le transport aérien afin d'améliorer les rotations obtenues. Lettovsky (1997) présente une approche intégrée pour les avions, les équipages, et la mise à jour de passagers. Cependant, il ne met en œuvre qu'une petite partie de cette approche intégrée. Il propose un algorithme basé sur la décomposition de Benders pour aborder cette intégration. Bratu and Barnhart (2006) présentent un problème de mise à jour des itinéraires de passagers tout en optimisant les coûts de blocs mensuels. Ils autorisent le retard ou l'annulation de certains vols, l'utilisation d'avions de secours ainsi que des membres d'équipage de réserve. Zhang and Hansen (2008) présentent un modèle pour un réseau *hub-and-spoke* intégrant divers modes de transport pour les passagers affectés. Abdelghany et al. (2008) proposent une approche intégrée au problème de mise à jour lorsque les retards de vol en raison de conditions météorologiques extrêmes sont considérés. Ils utilisent cette approche dans un cadre commercial. Ils prennent en compte l'intégration des horaires des avions, des pilotes et des agents de bord. Ils présentent des résultats numériques pour des scénarios avec un maximum de 1360 pilotes, et 2040 agents de bord. Les résultats montrent des solutions de bonne qualité, tant en termes de temps de résolution qu'en termes de coûts. La mise à jour simultanée pour les avions et les passagers a été la préoccupation centrale des recherches de Bisaillon et al. (2011) et de Jafari and Zegordi (2011). Petersen et al. (2012) présentent une technique de résolution basée sur un modèle mathématique et la génération de colonnes pour la mise à jour intégrée des vols, des avions, de l'équipage et des passagers. Ils donnent des résultats numériques pour une structure de réseau *hub-and-spoke* par un transporteur américain. Zhang and Lau (2014) présentent une formulation de partitionnement d'ensemble pour l'approche intégrée de mise à jour des vols, des avions et des équipages. Ils fournissent un algorithme en horizon fuyant pour résoudre ce problème. Ils donnent des résultats sur de petites et moyennes instances pour un transporteur américain.

# CHAPITRE 3 ORGANISATION DE LA THÈSE

Comme il a été mentionné dans la revue de la littérature, la planification des horaires anonymes a été l'approche la plus populaire en Amérique du nord, alors que le reste du monde opte pour une planification plus personnalisée. Afin de répondre aux certaines demandes de leurs employés, les compagnies aériennes nord-américaines ont commencé à utiliser de construire des horaires personnalisés. Ceci leur permet, d'une part, de réduire le nombre d'ajustement des blocs mensuels et, d'autre part, d'augmenter la productivité des employés puisque les contraintes de disponibilité et les préferences de chacun d'eux sont pris en considération lors de la construction des horaires. Dans ce cas, le problème personnalisé devient difficile à résoudre avec la méthode de génération de colonnes généralement utilisée. Le nombre de sous-problèmes qui est égal au nombre d'employés devient plus grand que le cas non personnalisé où il est égal au nombre de bases (Saddoune et al. 2012). La contribution principale de cette thèse est de proposer des approches qui résolvent le problème personnalisé pour pilotes et copilotes. Cette thèse comporte trois chapitres principaux dont chacun présente les résultats obtenus pour un objectif de recherche.

Le chapitre 4 présente l'article *Airline Crew Scheduling : Models, Algorithms, and Data Sets* où nous proposons une formulation mathématique du problème d'affectation des blocs mensuels personnalisés pour pilotes. Ce problème est résolu en utilisant une approche séquentielle où les rotations sont construites d'une manière anonyme, puis affectées aux pilotes en tenant compte les préférences de chacun d'eux lorsque c'est possible. Dans le contexte de cette thèse, nous considérons le choix des vols et des périodes de vacances comme deux types de préférences. Les résultats montrent qu'un niveau acceptable de satisfaction des pilotes peut être réalisé lorsque les blocs mensuels sont construits pour les pilotes via une approche séquentielle en utilisant la méthode de génération de colonnes.

La première contribution de ce chapitre est la présentation d'un modèle mathématique pour le problème de construction de blocs mensuels personnalisés. La seconde est le développement d'un logiciel construisant ce modèle contenant un sous-problème pour chaque employé. La troisième est la mise au point de stratégies d'accélération permettant de résoudre dans des temps raisonnables ces problèmes complexes et de grande taille.

L'article *Simultaneous Optimization of Personalized Integrated Scheduling for Pilots and Co-*

*pilots* est présenté dans le chapitre 5 où l'objectif est d'introduire une nouvelle formulation mathématique, qui n'avait pas été étudiée dans la littérature, et une approche de résolution qui intègre la construction des rotations et les blocs mensuels personnalisés pour pilotes et copilotes. Dans ce cas, les préférences et les contraintes personnelles conduisent à différents horaires mensuels pour pilotes copilotes. Toutefois, afin de maintenir la robustesse des horaires d'équipage sous perturbation au niveau opérationnel, les pilotes et les copilotes doivent avoir des rotations similaires lorsque cela est possible. Pour atteindre cet objectif, la construction des horaires est faite simultanément pour pilotes et copilotes à l'aide d'un algorithme heuristique qui essaie de satisfaire les préférences de chacun d'eux tout en minimisant des changements au niveau des rotations et des services de vols entre pilotes et copilotes. Les résultats obtenus montrent que l'approche intégrée satisfait plus les préférences que l'approche séquentielle. De plus, elle obtient des services de vols et des rotations communs entre pilotes et copilotes à 98%-99%.

La première contribution de ce chapitre est le modèle et l'algorithme traitant de façon intégrée les problèmes de rotations d'équipages et de blocs mensuels. La seconde est le traitement simultané des pilotes et des copilotes pour obtenir des services de vols et des rotations qui sont communs entre les pilotes et les copilotes. La troisième est l'algorithme heuristique qui permet d'obtenir de très bonnes solutions dans des temps raisonnables.

Le chapitre 6 présente l'article *Simultaneous Cockpit Recovery Problem*. La contribution de cet article réside dans l'élaboration d'une approche d'optimisation pour résoudre le problème de mise à jour intégrée. Cette approche intégrée considère en même temps les décisions sur la construction des rotations et l'affectation des blocs mensuels aux membres d'équipage et tient compte aussi des réglements relatifs aux rotations et aux horaires mensuels. Ce problème de mise à jour est résolu pour pilotes et copilotes simultanément afin de fournir des horaires plus robustes. En d'autres termes, en gardant pilotes et copilotes ensemble pendant chaque rotation, la propagation des perturbations à d'autres vols futurs est réduite. Les vols mis à jour sont considérés comme des données fixes pour le problème considéré. Au meilleur de notre connaissance, cet article présente une première tentative qui considère le problème de mise à jour simultanée pour pilotes et copilotes et qui traite de faç intégrée la mise à jour des rotations d'équipages et des blocs mensuels. Les résultats indiquent que l'algorithme de réoptimisation couvre les vols perturbés avec une augmentation de coût et une perte des préférences de vol acceptables. L'algorithme peut résoudre des cas contenant jusqu'à 610 pilotes et copilotes dans des temps de calcul raisonnables.

# CHAPITRE 4 ARTICLE 1 : AIRLINE CREW SCHEDULING : MODELS, ALGORITHMS, AND DATA SETS

Recopié avec permission. A. Kasirzadeh, M. Saddoune, F. Soumis, (2015), Airline Crew Scheduling : Models, Algorithms, and Data Sets. *EURO Journal on Transportation and Logistics*, publié le 27 fevrier 2015.

**Abstract**

The airline crew scheduling problem has received extensive attention, particularly in the last sixty years. This problem is frequently divided into crew pairing and crew assignment because of its large size and the complex safety agreements and contractual rules. Several solution methodologies have been developed, but many objectives and constraints are treated approximately and research is ongoing. In this paper, we present a comprehensive problem definition for the airline crew scheduling problem, and we review existing problem formulations and solution methodologies. In addition, we formulate the personalized cockpit crew scheduling problem as a set covering problem and we solve it using column generation. We present computational results for real data from a major US carrier, and we describe the data sets (available on the internet) in detail to establish a basis for future research.

## 4.1 Introduction

The airline industry and its operations has been a major focus of operations researchers, especially since the advent of the jet age in the late 1950s, which was followed by major technological advances. The industry has become a significant economic force from two perspectives : its own operations and its impact on related industries such as tourism and aircraft manufacturing. The revenue mainly comes from passenger tickets, while the costs include airplane expenses, fuel, crew, and equipment. The total profit is a complicated function of all of the operations. Data from the Air Transport Association (2008) indicate that the largest administrative cost is fuel expenses, and the second largest is labor costs (23.4%) (Belobaba et al., 2012). Minimizing the crew costs is therefore an essential task in today's competitive airline industry, and even a small reduction can lead to significant savings. In addition, the recent appearance of low-fare airlines has increased the pressure to provide affordable tickets and reemphasized the importance of minimizing expenses. As a result, the airline crew scheduling problem has received much attention in both industry and academia.

Airline crew scheduling is the problem of assigning a group of crew members to a set of scheduled flights such that all the scheduled flights are covered while the rules and collective agreements, imposed mainly by safety and labor organizations, are respected. The complex restrictions make this one of the most difficult crew scheduling problems in the transportation industry.

We present an extensive review of research into the airline crew scheduling problem, and we observe that authors do not compare their methods on the same data. We present a new model and solution approach for the personalized pilot assignment problem with pre-assigned activities and preferences that has not yet been introduced in the literature. Our model is a set partitioning model that we solve via column generation (CG). The remainder of this paper is structured as follows. In Section 4.2, we define the airline crew scheduling terminology that we use. Section 4.3 explains the different decision problems faced by airlines. In Section 4.4, we present an extensive review of airline crew scheduling. Section 4.5 discusses the different rules and agreements that generally apply. In Section 4.6, we give a detailed mathematical description of our problem, personalized pilot assignment, and Section 4.7 describes our solution approach in detail. In Section 4.8, we present numerical results for seven data sets. Our clear description of the problems (the rules and agreements) and the available data sets will allow other researchers to test their methods on the same data sets. In Section 4.9, we discuss the data sets and potential directions for future research. Section 6.7 presents concluding remarks.

### 4.2 Airline Crew Scheduling Terminology

In this section, we define the terminology that we use in our discussion.

– *Air leg* : A nonstop flight segment. Each air leg is characterized by five features : the flight number, the origin airport, the destination airport, the departure time, and the arrival time.
– *Deadhead* : An air leg in which a crew member flies as a passenger for relocation purposes.
– *Duty* : A sequence of consecutive air legs (and/or deadheads) comprising a working day for a single crew member. Two consecutive duties should begin and end at the same airport. Duties are separated by layovers.
– *Layover* : A rest period (an overnight stop) between duties that typically lasts for at least ten hours.
– *Pairing* : A sequence of duties and layovers for an unspecified crew member that starts and ends at a base. In short- and medium-haul problems, pairings typically last one to five days ; in long-haul problems, longer pairings are allowed.

- *Base* : A large airport. Each crew member is associated with a base, which means that all his/her associated pairings must begin and end at that airport.
- *Elapsed time* : A period of time in which a crew member is away from the base, referred to as Time Away From Base (TAFB).
- *Credited flying time in a duty* : The active flying time plus a specific percentage of deadhead flying time (typically 50%).
- *Monthly schedule (schedule)* : A sequence of pairings separated by time off that covers a given time horizon (usually a standardized planning month). In this paper, the term *schedule* refers to a monthly schedule.
- *Briefing time* : A period of time before the start of each duty that is spent on instructions and crew discussions with the goal of transforming a group of individuals into an effective team.
- *Debriefing time* : A period of time at the end of each duty that gives the crew members an understanding of the events that occurred and their implications.
- *Crew members* : Generally divided into two groups based on their role : the *cockpit crew members* are the pilot (captain), copilot (first officer), and flight engineer, all of whom are qualified to fly one or more aircraft types. The *cabin crew members* are the cabin captain and the flight attendants.
- *Post-pairing rest* : A rest period between two consecutive pairings that respects a minimum and a maximum duration.
- *Post-pairing* : A rest period between two consecutive pairings that contains a complete day off (from midnight to midnight).
- *Aircraft Route* : A sequence of air legs flown by a specific aircraft.

### 4.3 Airline Decision Process

Because of its complexity and the potential perturbations, most major airlines divide the overall decision problem into two closely related procedures : planning and recovery. Each procedure is then divided into several steps that are often treated separately. The planning procedure consists of flight scheduling, fleet assignment, aircraft maintenance and routing, and crew scheduling. The recovery procedure has three steps that adjust the plans to take into account unexpected perturbations : aircraft recovery, crew recovery, and passenger recovery (see Fig. 3.1).

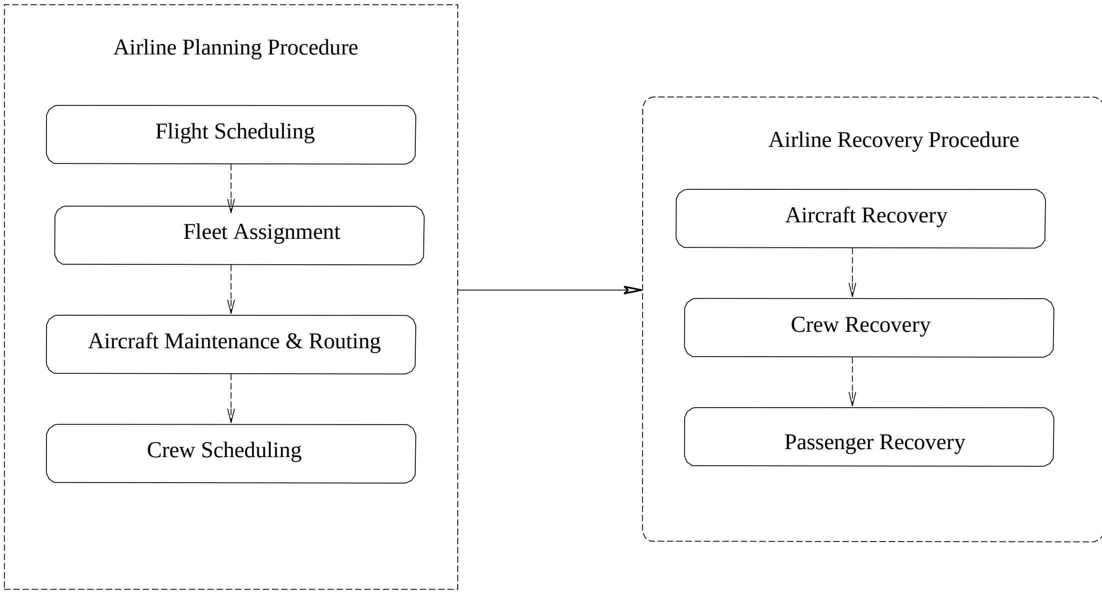


Figure 4.1 Airline decision process

### 4.3.1 Airline Planning Procedure

The steps of this procedure are interrelated, but because of their complexity they are often solved sequentially. The solution of each step becomes input data for the next step. Recently, some researchers have integrated two or more of these steps ; this is discussed in Section 4.4. The first step is the flight scheduling problem in which the air legs to be flown for a specific time horizon are scheduled with the objective of maximizing the expected profit. In the second step, fleet assignment, the various aircraft types such as the Boeing 707 and the Airbus A318 are assigned to the flights, taking into account the estimated passenger demand, the aircraft availability, and aircraft flow conservation. In the third step, aircraft maintenance and routing, individual aircraft are assigned to each scheduled flight, and the solution ensures that each aircraft spends adequate time at specific airports for routine maintenance. The fourth step, crew scheduling, is separable by crew category and aircraft type or family. It finds crew schedules that cover all the scheduled flights and satisfy the constraints. As mentioned in Section 4.2, the *cockpit crew* fly the aircraft and the *cabin crew* are responsible for passenger services and safety. A member of one group cannot normally be substituted for a member of the other group. The two groups are scheduled separately for three reasons. First, each cockpit crew is qualified to fly a specific aircraft type or family, whereas cabin crews can be assigned to multiple aircraft types. Second, the number of cabin crew required depends on the number of passengers, whereas the size of the cockpit crew is fixed. Third, cockpit crews are paid substantially more than cabin crews because of their level of expertise. As a result, most of the research into crew cost optimization has focused on cockpit crew scheduling. Hereinafter, we refer to *cockpit crew members* simply as *crew members*.

Because of its complexity and size, the crew scheduling problem is usually separated into two steps : *crew pairing* and *crew assignment*. Traditionally, the steps have been treated sequentially. The *crew pairing* forms a minimum-cost set of anonymous feasible pairings from the scheduled flights such that all flights are covered exactly once and all the pairing regulations and contractual rules are respected. Different airlines have different rules, but the main characteristics of the anonymous pairings are common to all airlines. *Crew assignment* combines the anonymous pairings with rest periods, vacations, pre-assigned activities such as training, and other breaks over a standardized month to produce a set of individual schedules for the crew members. The schedules must satisfy all the safety regulations and contractual rules. In contrast to the crew pairing problem, the crew assignment problem is separable by crew base and fleet type, and one of two general approaches is used :

1. *Bidline schedules* are constructed anonymously and the airline then announces them to the crew members. The crew members bid on these schedules, and their bids are used to complete the schedule allocation.
2. *Personalized schedules* take into account the crew members' preferred tasks and their needs for special activities such as vacations and training periods. The pairings are combined to give monthly schedules respecting airline objectives and providing a certain level of crew satisfaction. Two types of personalized schedules are considered : *rostering* and *seniority-based*. *Rostering* aims to maximize global satisfaction and may consider a second objective of fairness, measured in terms of the number of satisfied preferences. *Seniority-based* personalized schedules give priority to the satisfaction of the more senior crew members.

Historically, bidline scheduling has been the most common approach in the US whereas personalized scheduling is more common in the rest of the world. However, personalized schedules are now increasingly accepted at North American airlines because they offer advantages for both crew members and airlines. From the crew member's perspective, this approach considers the employee's requests during the construction of the schedule. From the airline's perspective, this approach considers the predefined employee activities : vacations, training, and unfinished pairings from the previous month. This reduces the number of schedule adjustments and increases productivity.

### 4.3.2 Airline Recovery Procedure

In real life, there are many unpredicted disruptions that arise because of weather conditions, aircraft maintenance issues, crew problems, and other unplanned events. These can lead to delayed or cancelled flights, and they perturb the crew schedules.

When such disruptions occur, the airline recovery procedure updates the scheduled flights, aircraft routes, crew schedules, and passenger itineraries. The time horizon is short (usually one to four days). The recovery procedure is not the focus of this paper, and we do not discuss it further.

## 4.4 Review of Crew Scheduling

We now provide a comprehensive review of models and algorithms for airline crew scheduling. We discuss the different objectives such as cost minimization and employee satisfaction. As mentioned in Section 4.3.1, the crew scheduling problem is usually separated into two steps : crew pairing and crew assignment. The steps are usually solved sequentially. However, recently several researchers have explored joint optimization approaches. We do not discuss the heuristic acceleration techniques that are used in industry to solve large problems because there are many parameters that must be carefully adjusted, and this topic is beyond the scope of our paper.

Mathematically, crew pairing and assignment problems are usually modeled via the set partitioning problem (SPP) or the set covering problem (SCP) with additional constraints. The problems are difficult because of the number of constraints and variables ; they are large-scale mixed integer problems. The three most common solution methodologies are Lagrangian relaxation (Geoffrion (1974), Fisher (1981), Fisher (1985), and Martin (1999)), Benders decomposition (Benders (1962) and Minoux (1986)) and branch and price (Desaulniers et al. (1998), Desrosiers et al. (1995), and Barnhart et al. (1996)). Since the 1990s, the most popular approach has been the SCP with CG embedded in branch and bound (see Desrosiers and Lübbecke (2005), Desrosiers et al. (1995), and Barnhart et al. (1996)). This method will be discussed in Section 4.7.

Barnhart et al. (2003) provide an excellent literature review and a detailed survey of crew pairing problems. Gopalakrishnan and Johnson (2005) give a survey of different approaches and solution methodologies for airline crew scheduling problems. Desaulniers et al. (2005) surveys the models and algorithms for large-scale airline planning and operational problems, giving extensive references. More recently, researchers have explored the monthly pairing problem, the personalized assignment problem, and integrated crew scheduling. In this paper we survey the state-of-the-art of studied approaches and solution methodologies for the airline crew scheduling problem.

In Section 4.4.1, we provide a comprehensive review of the sequential crew planning problem, and in Section 4.4.2 we describe the models and algorithms for the integrated crew planning problem.

### 4.4.1 Sequential Crew Planning

Section 4.4.1 discusses the crew pairing problem and Section 4.4.1 discusses the crew assignment problem.

#### Crew Pairing

For a given crew category and fleet type, the crew pairing problem finds a set of minimum-cost pairings such that each scheduled flight over the time horizon is included in exactly one pairing. The solution approach depends on the airline's size, network structure (e.g., hub-and-spoke), rules and regulations, and cost structure. There are three traditional approaches. The *daily* problem assumes that the air legs are identical for all the days of the planning horizon, and the minimum-cost pairings are generated based on the scheduled legs for a single day. The *weekly* problem assumes that the air legs are repeated every week, and the pairing problem is solved based on the scheduled air legs for one week. The *monthly* problem has a time horizon of a full month. Recent research has focused on the weekly and monthly problems. Because of vacation periods and variations in the flight schedules, the monthly time horizon is the most realistic.

The crew pairing problem is typically formulated as an SPP or SCP in which each task (air leg) is a constraint and each feasible pairing is a variable. There are usually additional constraints that enforce the various restrictions, safety rules, and regulations such as the maximum flying time for each base. The number of feasible pairings is extremely large, so it is often impossible to consider all of them. The problem has therefore traditionally been treated in two steps : the first step generates a subset of good pairings by enumeration, and the second uses the SPP to select the best pairings of this subset. Initially, heuristic local-search algorithms were often used ; a typical example is presented by Marsten and Shepardson (1981). They present an SPP model and a solution technique based on Lagrangian relaxation and subgradient optimization. They report tests on data sets from the Flying Tiger Line, Pacific Southwest Airways, Continental Airlines, and Helsinki City Transport. Gershkoff (1989) presents an SPP that minimizes the cost for the daily pairing problem. Gershkoff introduces a heuristic algorithm in which possible pairings are constructed at each iteration for a subset of the scheduled air legs. The heuristic continues until no further improvement is possible or a stopping criterion such as a time restriction is satisfied. Results are presented for American Airlines. Anbil et al. (1991) use this approach in software for American Airlines called the Trip Reevaluation and Improvement Program (TRIP). They explain the advances that allow the software to solve large problems more quickly. This software was sold to ten other airlines.

Anbil et al. (1992) introduce a global approach with a cost-minimization objective. In this joint study by IBM and American Airlines Decision Technologies, millions of feasible pairings (columns) are enumerated a priori and several thousand are provided to the LP solver. At each iteration, most of the nonbasic columns are discarded and new columns are added. The process continues until all the columns have been taken into account. Bixby et al. (1992) combine the interior point and simplex methods to find the solution of the LP relaxation for very large problems. The experiments show that the hybrid approach is more efficient than applying either method separately. Hoffman and Padberg (1993) propose a branch-and-cut approach for an SPP in which pairings are generated heuristically a priori, and cuts are used to find an integer solution. They present results for sixty-eight data sets from four major airlines. The integrality gaps are large (up to 5%) and much effort is necessary to obtain a good integer solution. Klabjan et al. (2001) improve on the approach of Hoffman and Padberg (1993). They enumerate millions of random pairings. The relaxation is first solved and millions of columns are selected based on their reduced costs. The number is then reduced by a heuristic based on LP, and integer solutions are obtained using a commercial IP solver. The branching rule is enhanced by combining strong branching with a specialized branching rule. Experiments are reported for a large US airline.

Heuristic approaches have three major problems. First, they do not consider all the scheduled flights at once, and they usually perform several iterations before finding a reasonable solution. Second, they do not consider all the possible pairings. Third, they provide no information on how far the solution is from the optimal solution. Therefore, more sophisticated approaches for pairing generation have been proposed. Lavoie et al. (1988) present an SCP and propose an algorithm for the continuous relaxation of the problem based on generalized LP, generating columns via shortest-path subproblems. Experiments for instances with up to 329 air legs give good results. Desrosiers et al. (1991), Barnhart et al. (1994), Desaulniers et al. (1997), and Desaulniers et al. (1998) use CG to consider all the pairings instead of a subset of a priori generated pairings. They propose a dynamic CG approach (and a branch and price algorithm) that implicitly considers all possible pairings when solving the LP relaxation ; we explain this approach in more detail later. The integrality gaps become smaller (less than 1%) when all the feasible pairings are considered.

Wedelin (1995) introduces a dual coordinate search together with an approximation algorithm for large-scale 0-1 integer problems. The approximation scheme adjusts the costs as little as possible such that the new problem has an integer solution. The degree of approximation is determined by a parameter, and for different values of this parameter the algorithm can be interpreted in terms of LP, dynamic programming, or a greedy approach. It is applied to large-scale data sets extracted from the Carmen system (the model is the SCP). The results show that the algorithm compares well with CPLEX in terms of both computational time and solution quality. Andersson et al. (1998) give a general overview of the Carmen pairing-construction system that is used at most major European airlines. This system has been successful because it integrates manual and automatic approaches to scheduling, provides high-quality and robust optimization, and is user-friendly.

Vance et al. (1997) consider a model for a two-stage decision making process for the crew scheduling problem. In the first stage, they select a set of duty periods that cover the scheduled flights. They then construct the pairings based on these duty periods. They use a decomposition approach based on dynamic CG. Experiments are presented for a major US domestic airline : the new approach provides tighter LP bounds, but the solution process is more difficult. Barnhart and Shenoi (1998) solve an approximate model of the crew pairing problem and use the solution as the initial solution for conventional approaches. Promising results are presented for a long-haul airline. Hu and Johnson (1999) propose a primal-dual subproblem simplex algorithm to speed up the solution of the LP relaxation. Experiments are reported for instances with up to 930 air legs.

Hjorring and Hansen (1999) propose a black-box rule system to simplify the implementation of the various rules and regulations. They integrate CG with a pricing subproblem, based on a duty network and a $k$th shortest path algorithm. Results are provided for some realistic data sets. Subramanian and Sherali (2008) propose an effective deflected subgradient optimization scheme for generating good dual solutions for the LP problems. This approach, used together with CG, is embedded in the crew pairing solver at United Airlines. Tests using historical data sets show that significant benefits can be obtained by using this approach instead of a standard solver for the intermediate LPs. AhmadBeygi et al. (2009) consider a new IP approach that is easy to implement, facilitating prototyping and the testing of new ideas. Their proposed model uses connection variables and market variables to capture the nonlinear cost function and constraints. Results for data sets from a major US hub-and-spoke carrier demonstrate the performance of the approach. Dück et al. (2011) present a column- and cut-generation algorithm. The objective is to minimize the number of pairings to cover a set of scheduled flights with respect to the regulations, ignoring the duty duration. The problem is formulated as an SPP with shortest-path resource-constrained subproblems. This algorithm has been applied to some small and medium instances from a European airline. Saddoune et al. (2013) introduce a rolling-horizon approach to find the minimal-cost pairings for the SPP formulation of the monthly pairing problem. They discuss the weaknesses of the traditional approach in which daily, weekly, and monthly problems are solved sequentially. Experiments for a major short- and medium-haul US airline give good results.

**Crew Assignment**

There are several possible objectives for the problem of constructing monthly schedules (the crew assignment problem). Compared to crew pairing, crew assignment has received less attention.

In the context of the bidline assignment problem, Beasley and Cao (1996) present an IP formulation ; they use Lagrangian relaxation and subgradient optimization. This approach is embedded into a tree search to find the optimal solution. Results are provided for randomly generated test instances with up to 204 crew members and 500 tasks. Campbell et al. (1997) describe a bidline generator system for a US express transportation company (FedEx). The goal is to minimize the number of bidlines and the amount of flying time not assigned to bidlines. They use a metaheuristic algorithm based on simulated annealing. Jarrah and Diamond (1997) propose a heuristic SPP-based approach for the bidline assignment problem using a priori CG. The objective is to maximize the covered credit time while minimizing the number of bidlines. The system is semi-automatic : the user influences the subset of columns generated. This system is implemented in a major US airline, and good solutions are reported. Christou et al. (1999) introduce a two-phase approach based on genetic algorithms for bidline generation at Delta Air Lines. The objective is to maximize the average total value and the quality of the bidlines. The first phase of the algorithm aims to construct good bidlines, while the second phase completes the assignment by constructing valid bidlines, taking into account the pairings not covered at the first phase. The results, for up to 320 crew members, show that the algorithm provides significant savings compared to the semi-automated approach to bidline generation used at Delta Air Lines.

Weir and Johnson (2004) propose a three-phase approach for bidline generation. In the first phase, a mixed integer problem is solved to provide tentative bidlines (patterns). The second phase, based on an SPP, uses these bidlines to find final schedules that cover all the pairings. If phase two is not successful, phase three integrates the uncovered pairings into the schedules. Good results for up to 150 crew members are presented. K. et al. (2010) describe two heuristic algorithms for solving the SPP-based bidline scheduling problem where, as far as possible, each bidline should have the same number of days off and paid hours (bidline with equity). The first heuristic is a standard branch-and-price algorithm that relies on a rounding procedure to obtain integer solutions. The second algorithm combines dynamic constraint aggregation (Elhallaoui et al., 2005) with the first heuristic. The results show that for the largest instances (up to 564 pilots and 2924 pairings), the dynamic constraint-aggregation heuristic gives solutions better than those of the standard branch-and-price heuristic.

For the rostering problem, Day and Ryan (1997) consider Air New Zealand's short-haul operations. In their approach, using integer programming, the days off are first allocated and then the pairings and other activities are assigned. The method leads to the efficient construction of good-quality schedules since most of the pairings are one-day assignments, and it has been used since 1993 for all short-haul flight attendant rosters at Air New Zealand. Gamache et al. (1999) describe a generalized SPP and a heuristic approach based on CG to find good integer solutions for the problem of constructing personalized schedules while maximizing satisfaction and considering pre-assigned activities. They use control strategies in the CG to reduce the computational time for large problems. Results for medium instances from Air France demonstrate the quality of the solutions, in terms of both cost and computational time. The acceleration strategies reduce the computational times by a factor of more than 1000. The resulting schedules are compared with schedules constructed by the CADET program (then in use at Air France), and the new schedules had fewer uncovered duties. El Moudani et al. (2001) propose a heuristic bi-criterion approach that takes into account the satisfaction of the crew members. This approach is combined with a genetic algorithm to produce minimum-cost schedules that achieve a specific level of crew satisfaction. Results for data from a medium-haul airline are given. König and Strauss (2000a,b) introduce a heuristic that implicitly enumerates schedules using propagation techniques. This approach is implemented in the SWIFTROSTER algorithm, and good results are achieved for medium and large European airlines. Fahle et al. (2002), Kohl and Karisch (2000), and Sellmann et al. (2002) describe the Parrot project (1997), which is based on CG and constraint programming. The master problem (the selection of schedules) is solved as an LP, and constraint programming is used to prune the search. Kohl and Karisch (2004) provide a comprehensive study of the Carmen crew rostering system that has been used at KLM since 1995. They highlight practical considerations relating to the production settings of crew scheduling systems. Maenhout and Vanhoucke (2010) use Dantzig–Wolfe decomposition and propose a metaheuristic scatter search algorithm to assign personalized rosters to each crew member while minimizing the total operational cost and achieving a required schedule quality. They compare their method with an exact solution approach based on branch and price and steepest-descent variable neighborhood search. Results are given for instances with up to 150 pilots and 800 pairings.

For the seniority-based personalized assignment problem, Gamache et al. (1998) study the preferential bidding problem, considering seniority for the assignment of personalized schedules to pilots and officers. At Air Canada about 75 different bids, e.g., for a weekend off, are available. Each employee associates a weight with each bid and these weights are used to calculate a score for the potential schedules. A *residual* problem is then solved for each employee, from the most senior to the most junior. This determines the maximum-score schedule for the current employee, taking into account the other employees and the set of unassigned pairings. The problem is modeled as an IP and is solved by CG embedded in a branch and bound tree. Results are presented for twenty-four data sets from Air Canada. This research resulted in a preferential bidding system (PBS) that has been used at Air Canada since 1995. Achour et al. (2007) introduce the first exact solution approach based on CG for the PBS. They solve a sequence of LPs in seniority order, and the schedules of the employees are fixed as the algorithm progresses. When a tentative maximum score for a crew has been established, they explicitly enumerate all the feasible schedules with that score for that crew member. Results for real data sets with up to 91 pilots indicate a substantial improvement in the solution quality.

### 4.4.2 Integrated Crew Planning

As explained in Section 4.3.1, solving the airline planning problem sequentially does not guarantee an optimal result for the overall planning problem. Recently, researchers have investigated integrating some of the steps. A summary of research on the integration of crew pairing with aircraft routing and/or fleet assignment is provided in Section 4.4.2. Section 4.4.2 discusses the integration of crew pairing and assignment.

#### Integrated Crew Pairing, Aircraft Routing, and Fleet Assignment

Cordeau et al. (2001), Cohn and Barnhart (2003), Mercier et al. (2005), and Chen et al. (2012) address the integration of aircraft routing and crew pairing. Sandhu and Klabjan (2007) and Gao et al. (2009) consider the integration of fleet assignment and crew pairing. Klabjan et al. (2002) consider the integration of flight scheduling, aircraft routing, and crew pairing. Mercier and Soumis (2007) integrate the aircraft routing, crew scheduling, and flight retiming problems. Papadakos (2009) proposes various integration models for the fleet assignment, maintenance routing, and crew pairing problems. Ruther (2010) studies the integration of aircraft routing, crew pairing, and tail assignment.

**Integrated Crew Scheduling**

Guo et al. (2006) introduce a heuristic algorithm for partially integrating crew pairing and crew assignment. It is based on aggregated time-space networks where the crew members are unevenly stationed among bases, and their availability changes dynamically during the planning period. The algorithm first generates a group of pairings that are separated by weekly rests. Some parts of these pairings are then rearranged into individual crew schedules. Results for a European airline indicate a significant reduction in the cost of the schedules. Zeghal and Minoux (2006) integrate crew pairing and crew scheduling for technical crew members and for airlines with short- and medium-haul air legs. They replace a large number of binary constraints with a smaller number of stronger constraints (clique constraints), which improves the computational time and solution quality. To improve the efficiency of the exact methods, a heuristic method based on a rounding strategy is embedded in a partial tree-search procedure. Results for TunisAir, where it is possible to enumerate all the feasible duties, indicate that good solutions can be obtained in a reasonable computational time. Souai and Teghem (2009) propose a hybrid genetic algorithm to integrate crew pairing and crew assignment. They use three heuristics to deal with the regulations. Results for three data sets demonstrate the success of the approach.

Deng and Lin (2011) use the ant colony optimization algorithm to solve the crew scheduling problem. They formulate the problem as a traveling salesman problem on a weighted and constrained graph. Results for small real instances indicate that good solutions can be found. Saddoune et al. (2012) integrate the crew pairing and bidline crew assignment problems for pilots ; the objective is to minimize the total cost and the number of pilots. They combine the dynamic constraint aggregation of Elhallaoui et al. (2005) with CG. Results for a major short- and medium-haul US airline show that the approach gives significant savings, but the computational times are higher than in the sequential approach. Saddoune et al. (2011) reduce the computational time of the algorithm of Saddoune et al. (2012). They introduce a bi-dynamic constraint aggregation method that uses the neighborhood structure when generating columns for the CG. The results confirm the reduction in the computational time. Azadeh et al. (2013) introduce a hybrid metaheuristic for the nonlinear optimization of a crew scheduling problem in which the objective is to minimize the total crew cost while respecting the regulations. They also propose two hybrid algorithms based on the genetic algorithm and ant colony optimization. They perform experiments on twenty randomly generated data sets of various sizes.

## 4.5 Regulations for Airline Crew Scheduling

Airlines must respect many regulations during the crew scheduling process. These regulations have three main sources (Barnhart et al., 2003). Many are imposed by governing agencies (e.g., FAA in the US) to ensure safety. Labor unions often influence the working conditions of the crew members. Finally, airlines impose some conditions ; for example, they may restrict the set of feasible solutions in order to obtain more robust schedules. We now discuss typical regulations on the duties, pairings, and schedules. In Section 4.7, we discuss the regulations imposed in our crew scheduling model.

### 4.5.1 Duties

There must be idle time between any two sequential air legs to allow for connections. There are lower and upper bounds on this interval. Briefing and debriefing times are often required at the beginning and end of each duty. There are also strict constraints on the total number of flying hours in a duty, and there is usually a maximum number of landings per duty.

### 4.5.2 Pairings

There is typically a maximum number of duties in a pairing, a minimum and maximum duration of the layovers between duties, a maximum TAFB, and a maximum pairing duration. In addition, all pairings should begin and end at a base. FAA imposes an 8-in-24 rule, which means that extra rest is required if a pairing contains more than eight flying hours in any twenty-four-hour period.

### 4.5.3 Monthly Schedules

There are typically restrictions on the maximum number of flying hours per month, the minimum and maximum number of working days, the minimum number of days off, etc. There may be additional constraints relating to the needs and preferences of the crew members.

## 4.6 Description of Personalized Pilot Assignment Problem

The problem of constructing pairings and assigning personalized schedules to the crew members varies from one airline to another, depending on the regulations, the pre-assigned activities, and the extent to which the preferences of the crew members are taken into account. The pre-assigned activities are training periods, annual leave, medical appointments, and pre-assigned vacations. An example of an assignment problem for which the pre-assigned activities are taken into account is given by Gamache et al. (1999) for cabin crew members. The crew preferences may contain a large number of factors. The factors considered may vary from one company to another, and the objectives may also vary. The objective can be a weighted sum of factors or may be based on equity between crew members with priority given to the most senior employees (Gamache et al., 1998). We will present a simple case and a basic algorithm to solve large-scale problems with heuristics to speed up the solution process.

We solve the personalized monthly assignment problem for a fixed number of pilots based on a set of anonymous pairings. These pairings are the results of the experiments of Saddoune et al. (2013). The number of pilots comes from the solution of the bidline assignment problem in the sequential context by Saddoune et al. (2012). We assume that the airline allows two types of preferences : *vacations* and *preferred flights*. Each month, some of the pilots are asked to specify their preferred vacation period (if they wish to take a vacation in that month). The other pilots will be invited to enter vacation requests in other months. Each pilot also has the option of choosing a set of preferred air legs from the scheduled flights corresponding to the pairings associated with his/her base. The details of these two categories of preferences are given in Section 4.8.2.

We use the sequential approach that is common in the airline industry. Our approach differs from that of Saddoune et al. (2012) because we consider crew preferences. The problem of constructing anonymous pairings using a rolling-horizon approach has been solved by Saddoune et al. (2013). They also consider the problem of sequential bidline scheduling (Saddoune et al., 2012) in which they construct anonymous schedules for pilots that minimize the total cost and the number of pilots per base. They provide their results for the set of instances that we consider, and we use their results for the anonymous set of pairings (Saddoune et al., 2013) and the number of pilots per base obtained from solving the bidline assignment problem (Saddoune et al., 2012) for our personalized assignment problem. Furthermore, we use the same solution methodology based on CG, but we solve an enhanced mathematical model for the personalized monthly assignment problem. We assume a fixed number of pilots per base. Given the pilot preferences and the anonymous pairings, we construct personalized schedules that cover the pairings, minimize the total crew cost, and satisfy a minimum number of the preferences (preferred air legs and vacations).

Instead of considering the preferences and minimizing the cost in two separate steps, we combine the two factors into a single objective function to provide a unique SCP formulation for our problem. Section 4.6.1 introduces the notation that we use and Section 4.6.2 discusses the personalized assignment problem.

### 4.6.1 Notation

The notation is as follows :

**Sets**

$F$ : set of all scheduled flights to be covered ;

$L$ : set of all pilots ;

$V_l$ : set of preferred vacations for pilot $l \in L$ ;

$P$ : set of pairings ;

$S_l$ : set of all feasible personalized schedules for pilot $l \in L$ ;

$B_l$ : set of preferred flights for pilot $l \in L$ ;

**Parameters**

$C_p$ : cost of pairing $p \in P$ ;

$\bar{C}_f$ : penalty cost for not covering flight $f \in F$ ;

$C_s^l$ : cost of schedule $s \in S_l$ for pilot $l \in L$ ;

$n_s^l$ : number of preferred flights in schedule $s \in S_l$ for pilot $l \in L$ ;

$c_f^l$ : bonus cost for covering preferred flight $f \in B_l$ ;

$c_v^l$ : penalty cost for not covering preferred vacation $v \in V_l$ ;

$u$ : minimum number of preferred flights in schedules ;

$w$ : minimum number of preferred vacations to be covered ;

$$e_p^{s,l} = \begin{cases} 1 & \text{if pairing } p \in P \text{ is covered by pilot } l \in L \text{ in personalized schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

$$\bar{e}_p = \begin{cases} 1 & \text{if flight } f \in P \text{ is not covered} \\ 0 & \text{otherwise}\,; \end{cases}$$

$$e_f^p = \begin{cases} 1 & \text{if flight } f \in F \text{ is covered by pairing } p \in P \\ 0 & \text{otherwise}\,; \end{cases}$$

$$v_v^{s,l} = \begin{cases} 1 & \text{if vacation } v \in V_l \text{ for pilot } l \in L \text{ is covered by schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

**Variables**

$$x_l^s = \begin{cases} 1 & \text{if schedule } s \in S_l \text{ is chosen for pilot } l \in L \\ 0 & \text{otherwise}; \end{cases}$$

### 4.6.2 Personalized Assignment Problem

Given a minimum-cost set of pairings that covers all the scheduled flights in the planning horizon, the personalized pilot assignment problem finds minimum-cost schedules such that the pairings are covered exactly once and at least given numbers of the flight and vacation preferences are satisfied.

The cost of each schedule has fixed and variable components. The variable costs are the costs of covering the pairings, bonuses for satisfying the preferred flights, and penalties for not covering the preferred vacations; the fixed costs are the fees paid to the pilots. The costs of the pairings are given by Saddoune et al. (2012).

A global constraint is defined to ensure that a minimum number of the vacation preferences is satisfied. We add a bonus factor (a negative cost) for each flight preference that a schedule includes. The cost of covering the air legs is set to 0. The cost of personalized schedule $s$ for pilot $l$ is

$$C_s^l = \sum_{p \in P} e_p^{s,l} C_p + n_s^l . c_f^l + \sum_{v \in V_l} (1 - v_v{}^{s,l}) . c_v^l .$$

The SCP formulation is

$$\sum_{l \in L} \sum_{s \in S_l} C_s^l x_l^s + \sum_{f \in P} \bar{e_p} \bar{C_f} \tag{4.1}$$

$$\sum_{l \in L} \sum_{s \in S_l} e_p^{s,l} x_l^s + \bar{e_p} = 1, \qquad \forall p \in P \tag{4.2}$$

$$\sum_{l \in L} \sum_{f \in B_l} \sum_{s \in S_l} \sum_{p \in P} e_f^p e_p^{s,l} x_l^s \geq u \tag{4.3}$$

$$\sum_{l \in L} \sum_{s \in S_l} \sum_{v \in V_l} v_v^{s,l} x_l^s \geq w \tag{4.4}$$

$$\sum_{s \in S_l} x_l^s \leq 1, \qquad \forall l \in L \tag{4.5}$$

$$x_l^s \in \{0, 1\}, \qquad \forall l \in L, \forall s \in S_l \tag{4.6}$$

The objective function (1) minimizes the total cost of the schedules and penalty costs for uncovered flights. Constraint (2) ensures that each pairing is covered exactly once. Constraint (3) is a global constraint on the minimum number of preferred flights. Constraint (4) is a global constraint on the minimum number of satisfied vacation preferences. Constraint (5) ensures that at most one schedule is chosen for each pilot, and constraint (6) is the integrality condition.

## 4.7 Algorithm

Because of the large number of variables, we apply CG, which is embedded in a branch and bound scheme (branch and price) to obtain integer solutions. This method was pioneered by Desrosiers et al. (1995), Barnhart et al. (1996), and Desrosiers and Lübbecke (2005). Optimality can be achieved for small problems, and a near-optimal solution (usually within 1% of optimality) can be found for large problems. The rules and regulations for constructing monthly crew schedules (as explained in detail in Section 4.5) are simplified to make it possible to obtain optimal solutions for the LP relaxations (for instance the 8-in-24 rule is not implemented). The computational time to optimally solve the LP relaxation of the simplified problem is similar to the time used in industry to approximately solve the complete problem. This is a good choice for benchmark because it removes the violations on results due to approximate solutions and permits to have clear view of the affects of algorithms and their parameters.

In Section 4.7.1, we describe the CG, and in Section 4.7.3 we discuss the approach used to find integer solutions.

### 4.7.1 Column Generation

CG is considered one of the most significant advances in the solution of large-scale linear mixed integer models (Desaulniers et al., 2005). It is an optimal iterative method for LPs with a large number of variables.

The linear relaxation of the personalized assignment problem (1)–(6) is called master problem (MP). At each iteration, we consider a restricted master problem (RMP) that contains a subset of the variables (columns). The RMP is solved by a standard LP algorithm such as the simplex method and finds an optimal objective-function value and a pair of primal and dual solutions. Given the optimal dual solution from the RMP, the current subproblem tries to find columns with negative reduced costs. If such columns are found, they are added to the RMP for the next iteration. Each subproblem corresponds to a resource-constrained shortest path problem and is usually solved by dynamic programming. When no variable with a negative reduced cost can be found, the optimal solution for the RMP is optimal for the MP. In practice, the CG is often stopped before optimality is attained because of slow convergence (the tailing-off effect).

In Section 4.7.2, we describe the subproblems for the personalized assignment problem. Section 4.7.3 discusses our method for finding integer solutions.

### 4.7.2 Personalized Assignment Subproblem

There is one CG subproblem for each pilot in the personalized assignment problem. The subproblem is defined on a directed acyclic time-space network $G^l = (N^l, A^l)$, where $N^l$ and $A^l$ represent the node and arc sets for pilot $l$, respectively. Each network corresponds to a shortest path problem with resource constraints, and the goal is to find schedules with negative reduced costs. These subproblems are solved using a label-setting algorithm (Irnich and Desaulniers, 2005). The network $G^l$ is an enhancement of the bidline assignment network proposed by Saddoune et al. (2012) in the sequential context. It contains the arcs for preferences. Fig. 3.2 gives a partial illustration of the network (some of the nodes and arcs have been omitted).

The network has five node types. The unique *source node* and *sink node* represent the start and end of the schedules, respectively. Each pairing is specified by a *pairing start node* and a *pairing end node*. *Midnight nodes* specify the midnights of the planning horizon. The horizon starts and ends at midnight.

There are eight arc types. A single *schedule start arc* connects the source node to the first midnight node of the horizon and represents the start of the schedule ; its cost is 0. *Pairing start arcs* link each potential midnight node to the pairing start node at the base station ; their cost is 0. For each pairing, a *pairing arc* links the node at the beginning of the pairing to the node at the end of the pairing. Its cost is calculated based on the pairing cost function of Saddoune et al. (2012). A *preferred vacation arc* links two midnight nodes in the pilot's network if he/she has a vacation preference ; its cost is 0. We assume that the vacations start and end at the pilot's base station and that vacations occur between two midnights (e.g., a vacation may start at 00 :00 on the second day of the month and finish at 00 :00 on the tenth day). A *post-pairing rest arc* links the end pairing node at the base station to the start node of a subsequent pairing provided the intervening time is greater than the post-pairing rest. A *post-pairing arc* links the end node of the pairing to the first midnight node at the base station that permits a complete day off. A *day-off arc* links a pair of consecutive midnight nodes at the base station. The cost of these three arcs is 0. Finally, a *schedule end arc* connects the last midnight node in the horizon to the sink node and represents the end of the schedule.

In addition to constraints (2)–(6), the local restrictions are enforced via the resource constraints.

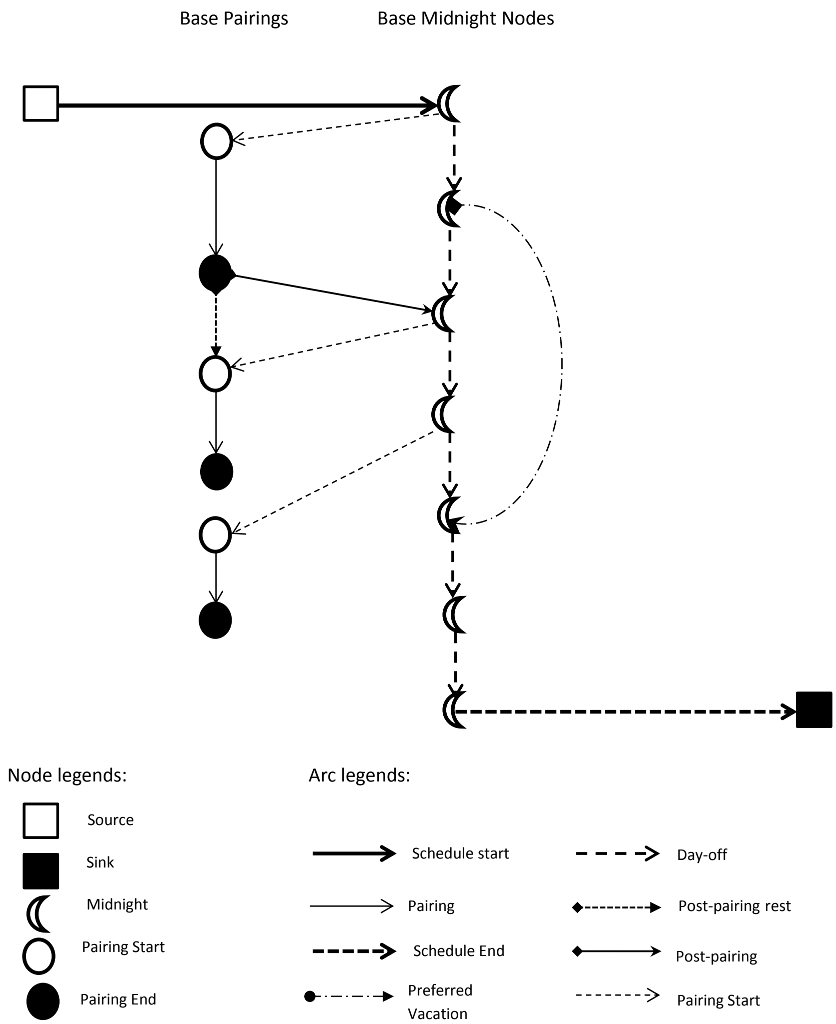


Figure 4.2 Directed acyclic time-space network for personalized assignment subproblem

There is a lower bound on the minimum number of days off in a schedule and a maximum number of consecutive working days. There is also a maximum credited flying time per schedule (85 hours for our tests).

The cost of a feasible path starting from the source node and ending at the sink node corresponds to the cost of a schedule and is equal to the sum of the arc costs on the path. However, the subproblem tries to find paths with a negative reduced cost so the arc costs should sum to the reduced cost of the associated pairing. Therefore, the arc costs are updated based on the dual variables and the coefficients of the variables in the MP constraints. The pricing in the personalized assignment subproblems is carried out via a multi-label shortest path algorithm (Desrosiers et al., 1995; Irnich and Desaulniers, 2005). A label is associated with each partial path originating from the source node. This label has a component for each resource and one for the reduced cost. The resource components give the value of the resource at the last node of the partial path, and the reduced-cost component indicates the reduced cost of this path. The initial labels are set to 0 at the source node. Before adding a new arc $m$ to a partial path, we check that the resource labels are within the upper and lower bounds of the resource windows at the start node of arc $m$. When adding an arc to an existing partial path, we recalculate the labels via extension functions, and the arcs with infeasible resource values are discarded. For large networks, the number of labels can be extremely large, and this can lead to long computational times at each CG iteration. To avoid this, we use a label dominance rule to discard suboptimal paths : label $L_1$ is dominated by label $L_2$ if both the resource and reduced-cost components of $L_1$ are less than or equal to those of $L_2$ (at least one inequality should be strict).

### 4.7.3 Integer Solution

After solving the linear relaxation of (1)–(6), we must find an integer solution. We embed the CG in a heuristic branch and bound scheme : at each branch and bound node, the lower bounds are calculated by CG. A fixing procedure is used to impose permanent decisions. Of the five branching strategies implemented in the GENCOL software that we use (two optimal strategies and three heuristics), we apply the two heuristic strategies : column fixing and heuristic inter-task fixing. Column fixing simply fixes a subset of the variables (columns) of the MP to 1 when their score is greater than or equal to a predetermined threshold. At each branching node, a score is calculated for each potential branching strategy. Through two parameters, the maximum and minimum scores, we map these scores to a scaled score. We compare the scaled scores and select the branching strategy with the better score. We use 0.85 as the threshold. If no suitable variable exists, two tasks (air legs for the pairing problem or pairings for the assignment problem) are assigned to the same pairing/schedule and are performed consecutively.

## 4.8 Computational Results

In this section, we present results for the personalized pilot scheduling problem based on monthly flight schedules operated by short- or medium-haul aircraft. Seven data sets are provided by a major North American airline. In Section 4.8.1, we describe the seven instances. Section 4.8.2 explains how we generate the preferences, and Section 4.8.3 gives the results for the personalized assignment problem.

The anonymous pairings are extracted from the results of the rolling horizon/CG approach of Saddoune et al. (2013). They consider a three-day time slice and a 1.5-day overlap between two consecutive slices. We determine the number of pilots for each instance from the results of Saddoune et al. (2012) for the sequential bidline scheduling problem.

### 4.8.1 Description of Data Sets

All 7 instances have 3 crew bases, and the number of flights ranges from 1013 to 7765. The number of stations varies between 26 and 54. Table 5.1 shows the characteristics of these instances. For the feasibility of the pairings, Saddoune et al. (2012) use the parameter values of Mercier et al. (2005), and for the feasibility of the schedules, they use the parameter values of K. et al. (2010). We use the same values for our tests. In addition, for the personalized assignment problem, we define some new parameters including a bonus for covering preferred flights and a penalty for failing to cover the preferred vacations. The costs of failing to cover flights, the preferred vacations, the preferred flights, and the cost of covering flights are all related. To show the relationship between covering flights and the preferences, we use the following example. We assume that it is more important to cover the scheduled flights than to satisfy the vacation and flight preferences. We assume that the cost of covering a scheduled flight is 0, and we set the cost of failing to cover a scheduled flight to 10000. The results show that this cost is large enough to ensure that the percentage of uncovered flights is very small. The cost of failing to satisfy a vacation preference is set to 1000. This cost is large enough to ensure appropriate satisfaction of the requested vacations and to avoid a large number of uncovered flights. We apply a negative cost (a bonus) of -100 for covering a flight preference to help satisfy the global constraint on the minimum number of preferred flights. It is important to mention that the costs of preferences are not very sensitive parameters; constraints (3) and (4) ensure a minimum number of preferred vacations and preferred flights.

Tableau 4.1 Characteristics of Instances

| | No. of Scheduled Flights | No. of Stations |
|---|---|---|
| $I1-727$ | 1013 | 26 |
| $I2-DC9$ | 1500 | 35 |
| $I3-D94$ | 1854 | 41 |
| $I4-D95$ | 5613 | 49 |
| $I5-757$ | 5743 | 34 |
| $I6-319$ | 5886 | 52 |
| $I7-320$ | 7765 | 54 |

We did not have access to real preference data for these data sets, so we randomly generated simple pilot preferences with parameters based on the expertise of analysts who have worked on data from more than 20 airlines. We now discuss the random generators.

### 4.8.2 Random Generators

We developed a random generator for the vacation preferences and another for the flight preferences, assuming that the scheduling month is a typical month outside of the high season.

#### Vacation Generator

In this random generator, the vacations are uniformly distributed during the month. Since the scheduling month is not a month with special events (e.g., Thanksgiving, Christmas), this assumption is reasonable. Each month, about 30% of the pilots, with variations due to integer rounding, request a vacation, and the duration ranges from 2 to 15 days. These numbers correspond to values observed in the industry.

Our experiments show that we can satisfy at least 38% of these requests ; a penalty is associated with each unsatisfied request. The vacation days are consecutive, and the vacations start and end at the pilot's base.

#### Flight Preference Generator

In this random generator, each pilot selects a specific percentage of preferred flights from the set of scheduled flights included in the pairings corresponding to his/her base. The selection follows a uniform distribution. For our experiments, we assume that each pilot prefers 10% of the scheduled flights.

We ensure that at least 20% of the flights contained in the pilots' schedules are preferred flights. We do not specify a minimum acceptable percentage of preferred flights for each pilot, because the pairings are constructed anonymously and the personalized schedules are constructed based on these pairings.

### 4.8.3 Summary of Results

Section 4.8.3 presents a summary of the results of Saddoune et al. (2012) for the pairing and bidline assignment problems. Section 4.8.3 discusses the results of solving the personalized assignment problem.

#### Pairing and Bidline Assignment Problem

Table 4.2 presents the results of Saddoune et al. (2012) for the pairing and bidline problems. They conducted their experiments on a Linux PC equipped with an Intel Xeon processor clocked at 2.8 GHz, using version 4.5 of GENCOL and version 10.1 of CPLEX. We use the pairing results to clarify the set of pairings for each instance when constructing monthly personalized schedules. We also use the bidline results on the total number of pilots for each instance to approximate the number of pilots per base. In contrast to the model of Saddoune et al. (2012), our model does not minimize the number of pilots. Instead, we assume a fixed number of pilots per base. Given a list of preferences for each pilot, we want to satisfy their preferences while covering the pairings. The CPU times are given in minutes.

Tableau 4.2 Results for Pairing and Bidline Assignment Problems

| | No. of pairings | No. of pilots | CPU time (Pairing) | CPU time (Bidline) |
|---|---|---|---|---|
| $I1-727$ | 172 | 33 | 2.50 | 1.50 |
| $I2-DC9$ | 303 | 34 | 4.34 | 1.46 |
| $I3-D94$ | 274 | 47 | 9.14 | 2.26 |
| $I4-D95$ | 1079 | 145 | 393.58 | 129.02 |
| $I5-757$ | 1497 | 247 | 67.80 | 164.10 |
| $I6-319$ | 1187 | 223 | 154.75 | 105.25 |
| $I7-320$ | 1648 | 305 | 289.22 | 218.38 |

#### Personalized Assignment Problem

We conducted our tests on a Linux PC with an Intel(R) Core(TM) processor clocked at 3.40 GHz. All of our implementations are coded in C++, and version 4.5 of GENCOL is used. The RMPs are solved using CPLEX 12.4. Table 4.3 gives the number of pilots per base. As mentioned, we did not minimize the number of pilots and sometimes the total number of pilot schedules is slightly lower than the number of pilots assigned to a base ; the pilots without schedules become reserve crew members. Table 4.4 summarizes the solution process. *Number of pilots* indicates the number of subproblems for each instance. We have many more subproblems (one for each pilot) than Saddoune et al. (2012) deal with in the context of sequential bidline scheduling (three subproblems, one for each base). *Number of CG iterations* indicates the total number of CG iterations. *Number of branching nodes* indicates the total number of branching nodes in the branch and price scheme. *Gap* gives the percentage difference between the lower bounds (LP solutions) and upper bounds (integer solutions). *CPU time (in minutes)* indicates the total CPU time.

Table 4.5 reports the quality of the solutions. *Percentage of uncovered flights* indicates the percentage of scheduled flights that are not covered despite the large penalty that we impose. *Average Credited Flying Time (ACFT)* shows how many hours each pilot works on average. The credited time consists of the duration of the air legs, half of the duration of deadheads, a debriefing time for each post pairing, and a briefing and debriefing time for each post-pairing rest. *Preferred vacations* shows the percentages of pilots with satisfied vacation requests. *Percentage of preferred flights* shows the percentages of the preferred flights in schedules. This is a measure of the quality of the personalization.

Tableau 4.3 Number of Pilots per Base

| | B1 | B2 | B3 | Total |
|---|---|---|---|---|
| $I1-727$ | 7 | 20 | 6 | 33 |
| $I2-DC9$ | 10 | 9 | 15 | 34 |
| $I3-D94$ | 10 | 30 | 7 | 47 |
| $I4-D95$ | 42 | 78 | 25 | 145 |
| $I5-757$ | 141 | 101 | 6 | 247 |
| $I6-319$ | 117 | 66 | 40 | 223 |
| $I7-320$ | 158 | 96 | 51 | 305 |

Although the number of subproblems is high (between 33 and 305) the solutions are found in a reasonable time (0.16 minutes for the smallest instance and 184.76 minutes for the largest). The CPU times are lower than those for bidline assignment. This reduction in time is due to the faster CPU and/or the improved version of CPLEX we use. On average, 29.09% of the flights are preferred flights, and 13.76% of the pilots have preferred vacations in their schedules. On average, 0.41% of the air legs are not covered ; this is an acceptable figure. Reserve crew members can be assigned to the uncovered flights. Except for $I5-757$, the gap is smaller than 1%. For $I5-757$, the number of CG iterations and the CPU time indicates

Tableau 4.4 Summary of Solution Process for Personalized Assignment Problem

| | No. of Pilots | No. of CG iterations | No. of Branching Nodes | Gap (%) | CPU Time (min) |
|---|---|---|---|---|---|
| $I1-727$ | 33 | 239 | 7 | 0.00 | 0.16 |
| $I2-DC9$ | 34 | 1968 | 30 | 0.18 | 0.45 |
| $I3-D94$ | 47 | 466 | 14 | 0.02 | 1.81 |
| $I4-D95$ | 145 | 2417 | 129 | 0.38 | 47.59 |
| $I5-757$ | 247 | 4531 | 172 | 2.91 | 149.58 |
| $I6-319$ | 223 | 2975 | 168 | 0.49 | 75.31 |
| $I7-320$ | 305 | 4011 | 195 | 0.37 | 184.76 |

Tableau 4.5 Quality of Solutions

| | Uncovered Flights (%) | ACFT | Preferred Vacations (%) | Preferred Flights (%) |
|---|---|---|---|---|
| $I1-727$ | 0.00 | 68.75 | 15.15 | 25.90 |
| $I2-DC9$ | 0.00 | 75.76 | 14.71 | 24.27 |
| $I3-D94$ | 0.00 | 72.70 | 14.89 | 26.66 |
| $I4-D95$ | 0.04 | 74.70 | 14.48 | 36.37 |
| $I5-757$ | 1.81 | 81.12 | 12.55 | 25.00 |
| $I6-319$ | 0.14 | 76.75 | 14.35 | 39.13 |
| $I7-320$ | 0.86 | 81.65 | 10.16 | 26.32 |
| *Average* | 0.48 | 75.92 | 13.76 | 29.09 |

that this is a difficult instance. The gap of 2.91% confirms that it is difficult to find integer solutions for this instance ; this is because the branching strategies do not fully explore the branch and bound tree. In industry, when users are not satisfied with the quality of a solution (e.g., large gaps), they modify some of the parameters and resolve the problem ; we did not do this.

### 4.9 Future Directions for Airline Crew Scheduling

Airline crew scheduling remains an active and interesting area with several unexplored avenues for research. Pairing construction for a monthly planning horizon, rather than daily or weekly problems, is still a challenge. In addition, some difficult constraints are currently treated heuristically, and research could take into account more sophisticated industrial regulations such as the 8-in-24 rule. It would also be interesting to introduce more sophisticated types of preferences. Research into the integration of the crew pairing and crew assignment problems is ongoing. Robust scheduling in the presence of uncertainty and possible perturbations is another challenging problem. The scheduling of cabin crew has received less attention. Each flight requires many cabin crew members, and some may need specific qualifications (administrative level, language, safety). As a result, each cabin crew member must be considered individually. Another potential research area is the simultaneous construction of schedules for cabin and cockpit crews that include common duties and pairings for different types of crew members (pilots, copilots, flight attendants).

We have decided to make available our data sets, preference generators, and the two types of supplementary constraints. These data sets will permit the research community to compare different algorithms. Adding supplementary constraints is one way to improve the link between the crew pairing and the crew assignment problem. These constraints lead to better pairings and more productive crew schedules. Our collaborators at AD OPT have suggested two types of supplementary constraints, and we have developed two generators to produce these constraints. The first group of constraints restricts the number of credited flying hours per base during the pairing construction. Using the unconstrained pairings, we compile statistics on the total credited hours. Two parameters are considered. The first adds an allowance to the total credited hours ; the second controls the percentage of credited hours per base. We associate a maximum percentage of the total credited flying hours with the main base and evenly divide the remaining time between the other bases. The second group of constraints is stronger than the first group and controls the crew availability per base per day. Given a planning horizon and an unconstrained solution, we count the number of duties per day. A parameter adds an allowance to the total number of duties for each day of the horizon.

Another parameter controls the number of crew members per base per day. If these values are not integer, we round them up while preserving the total number of crew members. All the data sets and generators are available at `www.gerad.ca/en/papers/G-2014-22`.

### 4.10 Conclusion

We have provided an extensive review of the airline crew scheduling problem. We have also proposed a mathematical formulation for the personalized crew assignment problem in the context of a sequential approach (crew pairing followed by crew assignment). We constructed personalized schedules by associating a subproblem with each crew member. In our tests, the number of subproblems varies between 33 and 305. In the bidline problem for the same set of instances, a subproblem is associated with each crew base (giving a total of 3 subproblems), so the personalized assignment problem is more challenging.

Taking the crew preferences into account is common in European airlines and becoming more frequent in North American airlines. We considered two types of preferences, for flights and vacations, in the context of short- and medium-haul flights. The results show that an acceptable level of crew satisfaction can be achieved when monthly schedules are constructed for pilots via a sequential approach based on branch and price.

**acknowledgements**

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# CHAPITRE 5 ARTICLE 2 : SIMULTANEOUS OPTIMIZATION OF PERSONALIZED INTEGRATED SCHEDULING FOR PILOTS AND COPILOTS

A. Kasirzadeh, F. Soumis, M. Saddoune, M. Towhidi, (2014), Simultaneous Optimization of Personalized Integrated Scheduling for Pilots and Copilots. *Transportation Science*, soumis le 31 décembre 2014.

**Abstract**

The airline crew scheduling problem involves assigning a group of crew members to scheduled flights over a planning horizon (usually a month) while respecting safety rules and regulations. Because of its size and complexity, this problem is frequently solved in two steps, first crew pairing and then crew assignment. Therefore, the global optimization of the crew scheduling is not guaranteed, because the crew pairing problem does not take into account the scheduling constraints. The *integrated* crew scheduling problem builds the pairings and assigns the monthly plans to crew members in a single optimization step. The problem of integrated bidline scheduling (where the schedules are anonymous) for pilots has been investigated by Saddoune et al. In this paper, we deal with the integrated personalized crew scheduling problem in the planning context. In this case, personal preferences and constraints result in different monthly schedules for the pilots and copilots. However, to maintain the robustness of the crew schedules under perturbation at the operational level, the pilots and copilots must have similar pairings when possible. To achieve this, this paper proposes a new heuristic algorithm that solves the integrated scheduling problem for the pilots and copilots *simultaneously*. Each problem is formulated as a set partitioning problem, and the solution approach is based on column generation and constraint aggregation. We conduct computational experiments on a set of real instances from a major US carrier.

## 5.1 Introduction

Operations Research (OR) approaches have contributed extensively to the tools and solution methodologies for the large-scale decision problems faced by airlines. In this context, OR approaches aim to reduce the cost of the airline operations and increase the quality of the crew schedules. Because of its complexity and the likelihood of disruption, the airline decision process is frequently divided into two related procedures : *planning* and *recovery*. Desaulniers et al. (2005) and Belobaba et al. (2012) provide a detailed literature review and survey the models and algorithms for airline planning and operational problems. The planning for a specific month is carried out four to six weeks in advance. However, in real life, perturbations may occur because of the weather conditions, aircraft maintenance issues, crew problems, and other unplanned events. These perturbations may lead to delayed or canceled flights, affect the crew schedules, and alter passenger itineraries. The recovery procedure is designed to handle these perturbations and to recover the flight and crew schedules. This procedure is not within the scope of this paper, and we do not discuss it further.

Ideally, we would formulate the planning problem as a single optimization problem in which a generic, unified objective function maximizes the total expected profit of the airline. This ideal optimization problem would encompass all the planning steps and all the constraints and rules. In practice, however, because of its complexity, the problem is simplified. Each step is considered individually, and the output of one step is the input for the next. The airline planning problem is usually divided into four main steps : *flight scheduling*, *fleet assignment*, *aircraft maintenance and routing*, and *crew scheduling*. These steps are explained in more detail in Kasirzadeh et al. (2015).

In the literature, the crew scheduling problem is divided into two substeps, because of its size and computational complexity : *crew pairing* and *crew assignment* (Barnhart et al., 2003; Gopalakrishnan and Johnson, 2005; Kasirzadeh et al., 2015). Crew pairing is the problem of constructing anonymous pairings such that the cost of the pairings is minimized and the scheduled flights are covered. A *pairing* is a sequence of duties (working days) and layovers (overnight stops) for an unspecified crew member ; a pairing starts and ends at a base. In short- and medium-haul problems, pairings typically last one to five days ; in long-haul problems, longer pairings are also allowed. Each crew member is associated with a *base* located at a large airport. The crew assignment problem is separable by crew category and aircraft type (or family of types). The crew categories are *cockpit crew members* and *cabin crew members*. The cockpit crew members are trained to fly one or more aircraft types. The cockpit crew always contains a pilot and a copilot, and for some large aircraft a flight engineer is added. The cabin crew members (the cabin captain and the flight attendants) are responsible for passenger services and safety, and they can be assigned to multiple aircraft types. Cockpit crew are paid significantly more than cabin crew, because of the expertise needed for their assigned tasks. As a result, most crew scheduling research has focused on cockpit scheduling (the flight engineers are not taken into account).

Crew scheduling is usually solved as either a *bidline* or *personalized* assignment problem. In the bidline approach, monthly crew schedules are constructed anonymously and then assigned to crew members. A *schedule (monthly schedule)* is a sequence of pairings separated by time off. The crew members bid for their preferred schedules. The personalized assignment problem takes into account vacations and training periods as well as the crew preferences. This problem is either treated as *rostering*, which maximizes the global satisfaction of the crew members, or *seniority-based* scheduling, which maximizes the satisfaction of the crew members in seniority order. Personalized scheduling is increasingly accepted at North American airlines because it offers several advantages over bidline scheduling. Personalized scheduling considers the employee's requests during the construction of the schedule and takes into account predefined employee activities (e.g., vacations, training periods, unfinished pairings from the previous month). Furthermore, personalized schedules decrease the number of schedule adjustments at the operational level and increase productivity.

Solving the airline planning problem in multiple steps clearly does not give a fully optimal result. Recently, researchers have combined two or more of the steps in order to obtain better solutions.

In this study, we solve the crew scheduling problem in a single optimization step by constructing the pairings and monthly plans using an integrated approach. The integrated approach builds monthly plans directly from flights (not from pairings), considering the rules impacting the pairings and monthly schedules. It also considers a global cost function for the scheduling problem. It takes the preferences of the crew members into account, producing different monthly plans for the pilots and copilots. To preserve robustness, the pilots and copilots must have similar pairings when possible. To achieve this, we optimize the schedules for the pilots and copilots simultaneously, taking their preferences into account. To the best of our knowledge, this paper is the first to consider the simultaneous optimization of cockpit crew schedules where the pairings and personalized monthly schedules are constructed by an integrated approach. We solve the problem via column generation (CG). Figure 1 presents the general structure of the problem, including the four traditionally separate problems of pilot pairing generation, copilot pairing generation, pilot scheduling, and copilot scheduling.

We first provide a brief literature review of the integration of the different steps of the airline planning problem.

In the context of integrated flight scheduling and fleet assignment, Lohatepanont and Barnhart (2004) introduce models and heuristic algorithms. They present experiments on medium-sized data from a major U.S. airline. Sherali et al. (2010) propose a Benders decomposition approach ; they take flexible flight times, schedule balance concerns, and recapture issues into account. They provide results for small data sets from United Airlines.

In the context of integrated aircraft routing and crew pairing, Cordeau et al. (2001) describe a

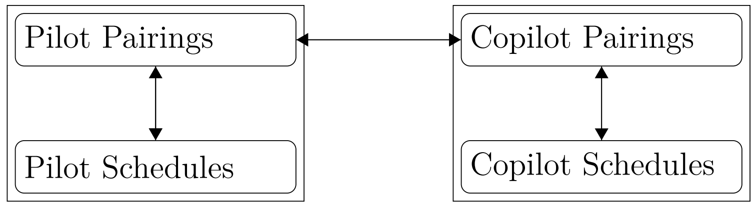



Figure 5.1 Schematic of personalized integrated scheduling for pilots and copilots simultaneously

set covering model. They propose an algorithm based on Benders decomposition and column generation, and good results are reported for a three-day horizon. Cohn and Barnhart (2003) introduce heuristic and optimal algorithms ; they report experiments on two small instances. Mercier et al. (2005) present two Benders decomposition approaches : one considers routing to be the master problem and the other considers pairing to be the master problem. Their experiments with data from two major airlines give good solutions. Weide et al. (2010) introduce a procedure that iterates between routing and pairing ; the solution of one step is used when the other step is being solved. This procedure tries to create robust solutions by reducing the number of crew and aircraft changes.

Sandhu and Klabjan (2007) present an integrated model for fleet assignment and crew pairing ; they neglect the aircraft maintenance constraints. They present two algorithms : 1) Lagrangian relaxation combined with column generation and 2) Benders decomposition. Results are provided for small instances. Gao et al. (2009) describe a model and algorithm for robust integrated fleet and crew planning. Their experiments give good results for data from a major U.S airline.

Klabjan et al. (2002) develop a model and algorithm for the integration of flight scheduling, aircraft routing, and crew pairing. They present good results for small instances. For the same problem, Papadakos (2009) introduces a set covering model and solves it via enhanced Benders decomposition combined with column generation. He reports good results for small data sets. Cacchiani and Salazar-González (2013) propose a heuristic and an algorithm based on column generation. They present results for small instances with no overnight flights.

The integration of the crew pairing and crew assignment problems has been investigated by Zeghal and Minoux (2006), Guo et al. (2006), Souai and Teghem (2009), Saddoune et al. (2012), and Saddoune et al. (2011). Zeghal and Minoux (2006) propose an integer linear programming model using clique constraints for integrated pairing and bidline assignment. They assume that the duties can be generated a priori, and deadheads can be introduced whenever required without extra cost. They solve the problem by two branch and bound algorithms, one exact and one heuristic, and present good results for small instances for a five-day horizon (with up to 101 flights and 40 crew) and a horizon of one month (with up to 195 flights and 18 crew). Guo et al. (2006) introduce a partially integrated crew scheduling approach based on pairing-chain generation. For each base, given the total number of crew members stationed at that base, they construct a series of *pairing chains* containing weekly rests and then adjust these pairings to take into account the crew requests and prescheduled activities. The tests are conducted for a 15-day horizon (with up to 1977 flights and 188 crew) and a 31-day horizon (with 808 flights and 44 crew). Souai and Teghem (2009) describe a genetic algorithm for integrated pairing and personalized assignment. They provide results for three small instances and a monthly planning horizon (with up to 1872 flights and 68 pilots). Saddoune et al. (2012) develop a model and algorithm based on column generation and dynamic constraint aggregation for integrated pairing and bidline assignment. They report good results for seven data sets from a major North American airline ; the largest has 7765 scheduled flights and 305 pilots. They report an average cost reduction of 3.37%, but the computational time was 6.8 times higher than that of the sequential approach. Saddoune et al. (2011) introduce different neighborhood strategies to reduce the size of the subproblems. The computational times are reduced by an average factor of 2.3 and the cost saving is 4.02% to 4.76%.

The main contribution of this paper is the construction of monthly personalized schedules via an integrated approach. These monthly schedules are for the planning context and are constructed for pilots and copilots simultaneously. We propose a new set partitioning formulation and a new heuristic algorithm. Our study is a generalization of the work of Saddoune et al. (2012). They studied the integrated anonymous scheduling problem for pilots and considered one subproblem for each crew base (three subproblems). Our study has a separate subproblem for each pilot/copilot because each crew member has different preferences (up to 610 subproblems). We present good solutions in terms of computational time for real-world problems.

There are four main goals in the crew scheduling problem : (i) minimizing the cost of pairings, (ii) minimizing the cost of monthly schedules, (iii) maximizing the global satisfaction of the crew members, and (iv) maximizing the number of common duties and pairings for pilots and copilots. These goals are considered at different steps of the decision process. In the sequential approach, the solution of the pairing problem considers only goal (i). The bidline assignment problem takes into account only goal (ii), and the personalized assignment problem considers goals (ii) and (iii). Both the bidline and personalized assignment problems satisfy goal (iv) because the pairings are not changed as the schedules are constructed, and they are the same for pilots and copilots. Integrated bidline scheduling considers goals (i) and (ii) and satisfies (iv) because the schedules are the same for pilots and copilots. Integrated personalized scheduling takes into account goals (i), (ii), and (iii). However, for goal (iv), it is important to solve the pilot and copilot scheduling problems simultaneously, so that the pilots and copilots have similar pairings whenever possible.

The remainder of this paper is structured as follows. Section 5.2 provides a detailed description of our problem and the proposed heuristic. Section 5.3 describes the mathematical formulation, and Section 5.4 describes our algorithm in detail. Section 5.5 presents results for three data sets, and Section 6.7 provides concluding remarks.

## 5.2 Problem Statement

The problem of constructing monthly schedules for airline crew members is different at different airlines, because the safety rules and regulations, preassigned activities, and crew preferences vary. In airlines where crew preferences are taken into account, there must be a trade-off between minimizing the cost of the crew schedules and satisfying the preferences of the crew members.

The cockpit crew scheduling problem is often solved under the assumption that the pilots and copilots are identical. In the context of bidline scheduling, this assumption is reasonable because the schedules are constructed anonymously and the crew preferences and preassigned activities are not taken into account. However, in the context of personalized scheduling, the pilots and copilots are not identical because they have different personal preferences. In this case, the *simultaneous optimization* of cockpit crew schedules becomes relevant. We simultaneously construct monthly schedules for cockpit crew members taking into account the four goals listed in Section 5.1. For robust schedules, it is necessary to keep a pilot-copilot pair together during duties and pairings whenever possible. There are four reasons for this. First, it helps to ensure the robustness of duties. If the pilot and copilot are separated when a perturbation occurs, the propagation effect will be greater. Second, it helps to ensure the robustness of the rest periods between the duties ; that is, crew members stay together during rest periods. Third, it helps to reduce the number of briefings and debriefings. Finally, it helps to reduce the costs of hotels and taxis when perturbations occur. We develop an algorithm that aims to build common pairings and duties for pilots and copilots, minimize the cost of the pairings, and provide a global level of preference satisfaction. The details of our algorithm are explained below.

We propose a heuristic approach that iterates between the *pilot scheduling problem (PSP)* and the *copilot scheduling problem (CSP)*. It is outlined in Figure 2.

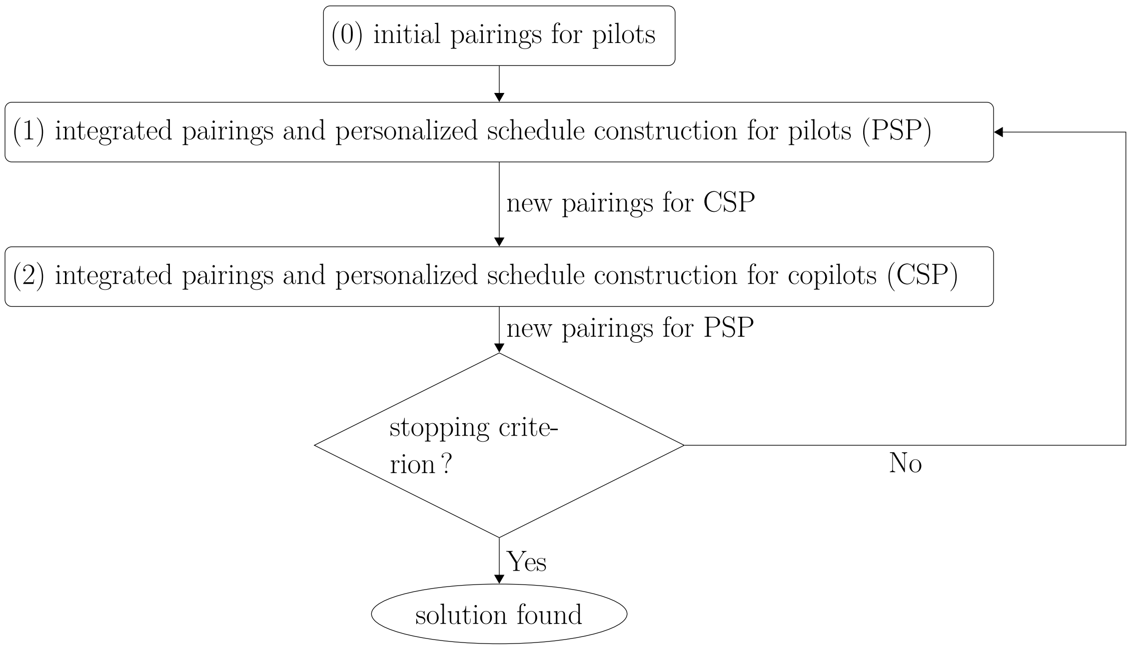



Figure 5.2 Heuristic algorithm flowchart for integrated crew scheduling problem

At each iteration of the algorithm, the personalized integrated scheduling problem is solved using the specialized DCA algorithm for the airline crew scheduling problem. The approach was developed by Elhallaoui et al. (2010) and specialized for airline crew scheduling problems by Saddoune et al. (2012). It is explained in Section 5.4. The objective of PSP (CSP) is to minimize the total cost of the monthly schedules for pilots (copilots) and to satisfy a global level of crew preferences. In our experiments, the two preferences that we take into account are *preferred vacations* and *preferred scheduled flights*. These preferences are generated by two random generators developed by Kasirzadeh et al. (2015). The heuristic algorithm stops when a stopping criterion is satisfied. It starts from a set of initial pairings (phase 0). For this set we use the anonymous pairings constructed by Saddoune et al. (2013) for the same set of scheduled flights and safety regulations. In the first phase we solve PSP and construct personalized monthly schedules for the pilots. The set of initial pairings is updated accordingly, and the new set of pairings is called NPP (new pairings for pilots). Taking NPP into account, in the second phase we solve CSP and construct personalized monthly schedules for the copilots. We call the new set of pairings NPC (new pairings for copilots). Given NPC, we solve PSP again to obtain an updated NPP. We then solve CSP again. This process continues until a stopping criterion is satisfied ; the criterion that we use is the maximum number of iterations. We need this because it may take a long time for the algorithm to converge. The results have a high level of similarity of pairings and duties for pilots and copilots.

There are two ways to encourage common sets of duties and pairings for the pilots and copilots. One option is to introduce *soft* constraints : bonuses for the common duties and pairings. The other is to introduce *hard* constraints ; this restricts the domain of exploration. The advantage of using hard constraints is the reduction in the computational time. In this study, we use hard constraints. Both the PSP and the CSP are mathematically formulated as set partitioning problems, as discussed in Section 5.3.

## 5.3 Mathematical Formulation

The integrated personalized cockpit crew scheduling problem is mathematically formulated using the following notation :

**Sets**

$F$ : set of scheduled flights ;

$P$ : set of feasible pairings ;

$L$ : set of pilots ;

$O$ : set of copilots ;

$V_l$ : set of vacation preferences for pilot $l \in L$ ;

$V_o$ : set of vacation preferences for copilot $o \in O$ ;

$G_l$ : set of preferred flights for pilot $l \in L$ ;

$G_o$ : set of preferred flights for copilot $o \in O$ ;

$S_l$ : set of feasible schedules for pilot $l \in L$ ;

$S_o$ : set of feasible schedules for copilot $o \in O$ ;

**Parameters**

$C_p$ : cost of feasible pairing $p \in P$ ;

$C^l_s$ : cost of personalized schedule $s \in S_l$ for pilot $l \in L$ ;

$C^o_s$ : cost of personalized schedule $s \in S_o$ for copilot $o \in O$ ;

$\bar{C}_f$ : penalty for not covering flight $f \in F$ ;

$n^l_s$ : number of preferred flights in schedule $s \in S_l$ for pilot $l \in L$ ;

$n^o_s$ : number of preferred flights in schedule $s \in S_o$ for copilot $o \in O$ ;

$c_f^l$ : bonus for covering preferred flight $f \in G_l$ for pilot $l \in L$ ;

$c_f^o$ : bonus for covering preferred flight $f \in G_o$ for copilot $o \in O$ ;

$c_v^l$ : penalty for not covering vacation preference $v \in V_l$ ;

$c_v^o$ : penalty for not covering vacation preference $v \in V_O$ ;

$$e_f^{s,l} = \begin{cases} 1 & \text{if flight } f \in F \text{ is covered by pilot } l \in L \text{ in schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

$$e_p^{s,l} = \begin{cases} 1 & \text{if pairing } p \in P \text{ is covered by pilot } l \in L \text{ in schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

$$e_f^{s,o} = \begin{cases} 1 & \text{if flight } f \in F \text{ is covered by copilot } o \in O \text{ in schedule } s \in S_o \\ 0 & \text{otherwise}\,; \end{cases}$$

$$e_p^{s,o} = \begin{cases} 1 & \text{if pairing } p \in P \text{ is covered by copilot } o \in O \text{ in schedule } s \in S_o \\ 0 & \text{otherwise}\,; \end{cases}$$

$$v_v^{s,l} = \begin{cases} 1 & \text{if vacation } v \in V_l \text{ is covered by schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

$$v_v^{s,o} = \begin{cases} 1 & \text{if vacation } v \in V_o \text{ is covered by schedule } s \in S_o \\ 0 & \text{otherwise}\,; \end{cases}$$

**Variables**

$$x_l^s = \begin{cases} 1 & \text{if schedule } s \in S_l \text{ for pilot } l \in L \text{ is chosen} \\ 0 & \text{otherwise}\,; \end{cases}$$

$$x_o^s = \begin{cases} 1 & \text{if schedule } s \in S_o \text{ for copilot } o \in O \text{ is chosen} \\ 0 & \text{otherwise}\,; \end{cases}$$

$$\bar{e}_f = \begin{cases} 1 & \text{if flight } f \in F \text{ is not covered} \\ 0 & \text{otherwise.} \end{cases}$$

At each iteration of the algorithm, we solve either the PSP (1)–(4) or the CSP (5)–(8).

$$\sum_{l\in L}\sum_{s\in S_l} C_s^l x_l^s + \sum_{f\in F}\bar{e}_f\bar{C}_f \tag{5.1}$$

$$\sum_{l\in L}\sum_{s\in S_l} e_f^{s,l} x_l^s + \bar{e}_f = 1, \qquad \forall f\in F \tag{5.2}$$

$$\sum_{s\in S_l} x_l^s \leq 1, \qquad \forall l\in L \tag{5.3}$$

$$x_l^s \in \{0,1\}, \quad \forall l\in L, \forall s\in S_l \tag{5.4}$$

$$\sum_{o\in O}\sum_{s\in S_o} C_s^o x_o^s + \sum_{f\in F}\bar{e}_f\bar{C}_f \tag{5.5}$$

$$\sum_{o\in O}\sum_{s\in S_o} e_f^{s,o} x_o^s + \bar{e}_f = 1, \qquad \forall f\in F \tag{5.6}$$

$$\sum_{s\in S_o} x_o^s \leq 1, \qquad \forall o\in O \tag{5.7}$$

$$x_o^s \in \{0,1\}, \quad \forall o\in O, \forall s\in S_o \tag{5.8}$$

Objective (1) (objective (5)) minimizes the total cost associated with the pilot (copilot) schedules. Constraints (2) (constraints (6)) ensure that each scheduled flight is assigned to exactly one pilot (copilot). Constraints (3) (constraints (7)) assign at most one schedule to each pilot (copilot), and constraints (4) and (8) are the binary requirements for the variables.

The cost of a schedule is composed of the cost of the pairings and the cost associated with the schedule quality. In practice, the cost of a pairing has a complex nonlinear structure and an approximate cost function is often used. The pairing cost function that we use was introduced by Mercier et al. (2005) and enhanced by Saddoune et al. (2013). It considers waiting, deadheading, and the duty cost to be the elements of a pairing cost.

The cost of a schedule can be any linear or, by extension, piecewise linear function, including preferences and fairness. For our experiments, we consider two types of preferences : preferred flights and preferred vacations. These preferences are translated into bonuses (for covering each preferred flight) and penalties (for not covering a preferred vacation). The cost of personalized schedule $s$ for pilot $l \in L$ is

$$C_s^l = \sum_{p\in P} e_p^{s,l} C_p + n_s^l c_f^l + \sum_{v\in V_l}(1 - v_v^{s,l})c_v^l.$$

The cost for copilot $o \in O$ is simply obtained by substituting $o$ for $l$. $C_s^l$ is a linear cost function, and we use it for our computational experiments. Fairness is rarely taken into account by North American airlines ; we do not consider fairness because we use data from a major North American airline.

### 5.4 Algorithm

Our algorithm is an enhanced version of CG embedded within branch and bound. CG is an iterative approach used to solve the relaxation of large-scale linear programming (LP) problems with set partitioning constraints (Desrosiers and Lübbecke, 2005; Desrosiers et al., 1995; ). Because of degeneracy, CG becomes inefficient when the number of set partitioning constraints is large and the columns are dense (with on average more than 8–12 nonzero elements ; see Elhallaoui et al. (2005)). In our problem, the number of nonzeros varies between 30 and 45. If more than 90% of the constraints of a large-scale LP are set partitioning constraints, DCA can be combined with CG to reduce degeneracy and accelerate the solution process.

DCA aggregates some of the set partitioning constraints at each iteration of the restricted master problem (RMP). The theoretical framework for DCA was introduced by Villeneuve (1999), and Elhallaoui et al. (2005) provided the first implementation. An *equivalence relation* is defined for the set $C$ of columns with positive values in the initial solution : two tasks $t_1$ and $t_2$ are *equivalent* if every column in $C$ covers both $t_1$ and $t_2$ or neither. We use this relation to form the tasks into *clusters*. DCA starts with a feasible or infeasible initial solution (obtained by a heuristic, by logical reasoning, or from a previous solution) and corresponding set $C$. The set $C$ is modified, when necessary, until an optimal solution is found. At each iteration, DCA changes the RMP to an aggregated restricted master problem (ARMP), which is smaller and easier to solve. Each cluster is considered as a constraint in the ARMP. We solve the ARMP by an LP optimizer and compute a pair of primal-dual solutions for the aggregated constraints. To generate columns for the original problem, we need a dual disaggregation process to provide dual solutions for each constraint of the RMP. We perform this disaggregation based on shortest-path calculations to provide a value for each set partitioning constraint of the original problem. The dual disaggregation is a complex process, and we do not discuss it in detail because it is not necessary for understanding our algorithm. For more information see Elhallaoui et al. (2005).

A *compatibility* criterion is defined between a partition Q and the path variables. A path said to be compatible with a partition if, for each cluster of the partition, it covers either all of the cluster's tasks or none. A newly generated column can be added to ARMP if it is compatible with the current partition. Otherwise, the variable is incompatible, and it can be added to ARMP only if the partition is modified ; this is because ARMP contains only compatible columns. The criterion for updating the partition is based on the relationship between the reduced cost of the least compatible column reduced cost (CCR) and the least incompatible column reduced cost (ICR). This relationship is such that CCR is less than

ICR times a predetermined multiplier $\Gamma$ ($\Gamma = 1$ for our tests).

To benefit from the current partition and the compatible variables, Elhallaoui et al. (2010) described a version of DCA with multiple phases (MPDCA) that favors the generation of compatible or slightly incompatible columns with respect to the current partition ; it uses a partial pricing strategy that favors slow disaggregation. To apply this strategy, we define a phase number ($h$) and an incompatibility number ($r$) for each column such that at phase $h$ only the incompatible variables with $r \leq h$ are priced out. The value of $r$ is an approximation of the number of additional clusters needed to make an incompatible column compatible. At the beginning of the solution process, we set the phase number to 0. We solve the ARMP and calculate the optimal primal and disaggregated dual solutions and the incompatibility number for each column. We then apply the partial pricing strategy and price out the columns with $r = 0$ (the compatible columns). When we find no negative-reduced-cost column, we increment $h$ and go to the next phase ($h+1$) or stop if $h$ is the final step. If negative-reduced-cost columns are found, we determine whether or not the current partition must be modified. If no change is required, we add all or a subset of the compatible columns to the ARMP, and the MPDCA moves to its next iteration. Otherwise, we update the partition.

In the algorithm of Saddoune et al. (2012) for the integrated bidline pilot scheduling problem, a cluster is a pairing, and a set of pairings that covers all the scheduled flights is a partition. Each column corresponds to a feasible monthly schedule for a pilot (or copilot). We use the improved MPDCA algorithm of Saddoune et al. (2012), which can be adapted for several subproblems, to solve the integrated personalized crew scheduling problem. Our initial set of pairings is the solution of Saddoune et al. (2013). MPDCA is exact if the last phase number k is sufficiently large to ensure the pricing of all feasible columns. Given the complexity of the problem, we use only k=0 and k=1 for our experiments. In other words, our MPDCA is heuristic. In practice, to avoid the well-known tailing-off effect, CG is stopped before optimality is reached. Two parameters determine the CG stopping criterion. We stop the CG if in the last $i$ iterations the objective value has decreased by less than a threshold value. These values are chosen based on preliminary tests : we stop the CG if within the previous 25 iterations, the objective value has decreased by less than 0.01%. This greatly reduces the search domain for the optimization. The new method starts with the sequential solution and improves it, and when we choose the above parameters we must find a trade-off between computational time and solution quality. Our results show that the sequential solution is substantially improved.

At each node of the branch and price tree, CG seeks a near-optimal linear relaxation solution. Two branching strategies are considered. The first fixes to 1 all the fractional values that are greater than a predetermined threshold (0.85 for our tests). The second forces two flights to be consecutive in a pairing. We choose the branching strategy for a given node by computing a score for each strategy and choosing the strategy with the higher score. Saddoune et al. (2012) showed that compared to the sequential approach, integrated bidline pilot scheduling reduces the cost by reducing the number of pilots and finding better schedules. Recall that our objective function is difficult. It minimizes the cost of the schedules, maximizes the satisfaction of the preferences, and encourages common pairings for pilots and copilots.

We can associate an acyclic directed time-space network $G = (N, A)$, where $N$ and $A$ are the node and arc sets, with each subproblem (i.e., each employee) of the PSP (and CSP). This network has five node types : source, sink, opportunity, departure, and arrival. It has twelve arc types : start of schedule, end of schedule, flight, deadhead, preferred vacation, rest, wait time, start of duty, start of pairing, day off, post-pairing, post-pairing rest. It is similar to the subproblem network in Saddoune et al. (2012). The difference is that in Saddoune et al. (2012) one subproblem is associated with each base, so there are just three subproblems. Because preferences vary from one crew member to another, we have one subproblem for each crew member, and so personalized scheduling is more complex than bidline scheduling (which has one subproblem per crew base). Furthermore, we have an additional arc type for preferred vacations.

In our experiments we do not have preassigned activities. However, if such activities are added, we can consider them as fixed activities ; that is, in the subproblem networks, we fix the arcs associated with preassigned activities and remove the arcs corresponding to other activities at the same time. Removing these arcs will decrease the size of the networks and facilitate the solution process.

To solve the subproblems we must find columns (shortest paths) with negative reduced costs that satisfy the resource constraints. Several local constraints and regulations are modeled by resources. A *resource* is a quantity that varies along a path. Each resource is distinguished by two characteristics : the *resource window* and the *resource consumption*. A resource window is associated with each node of the network. We build partial paths starting from the source node, and resource consumption occurs when an arc is added to the partial path according to the resource extension functions. We can add an arc only if the resource consumption of the new path is within the resource window of the new node. There are nine resources : maximum number of landings in a duty, maximum number of duties in a pairing, maximum working time in a duty, minimum working time in a duty, maximum duration of a duty, maximum pairing duration, minimum number of days off in a schedule, maximum number of consecutive working days, and maximum credited flying time. A feasible source-to-sink path (crew schedule) in a subproblem is a path that satisfies the resource constraints. For our subproblems, we use the resource values of Saddoune et al. (2012).

The subproblems are solved using dynamic programming. For resource-constraint networks, a multidimensional labeling algorithm is used (Irnich and Desaulniers, 2005). At the end node of each partial path, we consider a label with multiple elements, an element for each resource value and an element for the reduced cost. The labels are set to 0 at the source node. They are modified by label extension functions when an arc is added to a partial path. For large subproblems, many labels can be generated. To reduce the time for the path generation, we apply a *label dominance* rule that removes some partial paths. A partial path with end-node label $L_1$ is dominated by label $L_2$ if each component of $L_1$ is less than or equal to the corresponding component of $L_2$ (the value of at least one component should be strictly less).

We use a heuristic and an exact version of the label-setting algorithm of Saddoune et al. (2012) to solve the linear relaxations. At each LP iteration, we first use a heuristic in which the dominance rule considers the reduced cost along with a subset of the resources. This heuristic is relatively fast, but there is no guarantee that it finds the shortest path. If no negative-reduced-cost paths are found, an exact version uses all the resource components in the labeling algorithm. Based on the preliminary computational results, the following five resources are considered for the heuristic : maximum duration of a duty, maximum working time in a duty, minimum working time in a duty, maximum pairing duration, and maximum number of consecutive working days.

### 5.5 Computational Results

In this section, we present results for the integrated personalized cockpit crew scheduling problem for monthly flight schedules operated by short-haul aircraft. Three data sets are provided by a major North American airline ; they are described in Table 5.1. The initial pairings that we use in step (0) of the algorithm are the results of Saddoune et al. (2013), where the pairing problem is solved for the same data set. The number of pilots (and copilots) for each instance is the number of pilots in the solution of Saddoune et al. (2012) for the sequential bidline scheduling problem. We consider two types of preferences : vacations and preferred flights. The preferences are generated using the random generators developed by Kasirzadeh et al. (2015). The heuristic algorithm is implemented in C++, and version 4.5 of GENCOL is used. The RMPs are solved using CPLEX 12.4. We performed our tests on a computer equipped with an Intel(R) Core(TM) processor clocked at 3.40 GHz.

All the instances have three crew bases. For the feasibility of the pairings, we use the pa-

Tableau 5.1 Characteristics of Instances

| | $I1-727$ | $I2-DC9$ | $I3-D94$ |
|---|---|---|---|
| No. of Scheduled Flights | 1013 | 1500 | 1854 |
| No. of Pilots (Copilots) | 33 | 34 | 47 |
| No. of Stations | 26 | 35 | 41 |
| No. of Initial Pairings | 172 | 303 | 274 |

rameter values of Mercier et al. (2005), and for the feasibility of the schedules, we use the parameter values of Saddoune et al. (2012). In addition, we define some new parameters including a penalty for failing to cover a scheduled flight, a bonus for covering preferred flights, and a penalty for failing to satisfy a vacation preference. The costs of failing to cover scheduled flights, failing to satisfy vacation preferences, covering preferred flights, and covering scheduled flights are all related. We assume that it is more important to cover the scheduled flights than to satisfy the vacation and flight preferences. However, a very small percentage of uncovered flights is acceptable since most airlines have reserved cockpit crew members who can be allocated to uncovered flights. We assume that the cost of covering a scheduled flight is 0, and we set the cost of failing to cover a scheduled flight to 10000. Our results show that this cost is large enough to ensure that the percentage of uncovered flights is very small. Our preliminary results suggest a penalty of 5000 for failing to satisfy a vacation preference and a bonus of $-50$ for covering a preferred flight. These values ensure that a good percentage of the preferences are satisfied while the gap stays small and the percentage of uncovered flights remains very small.

In the first group of tests we consider variations of the penalty for failing to cover vacation preferences. The bonus for preferred flights is set to $-50$ and the vacation penalty varies between 1000 and 6000. The results for the three instances are given in Tables 5.2, 5.3, and 5.4. In each table, the first two rows give the penalty and bonus values. The *pairing similarity* is the percentage of common pairings at the last iteration, and the *duty similarity* is the percentage of common duties at the last iteration. The *total no. of CG iterations* is the total number of CG iterations in the three iterations. The *total CPU time* is the total CPU time of the three iterations. The *gap* is the percentage difference between the lower bounds (LP solutions) and the upper bounds (integer solutions). *Uncovered flights* is the percentage of scheduled flights that remain uncovered at the end of the process despite the penalty.

To evaluate the quality of the solution, we use two indicators : the *preferred flights* and the *satisfied vacation preferences*. Increasing the penalty for failing to satisfy vacation preferences increases the percentage of satisfied preferences. However, a trade-off occurs when we allow a very small percentage of uncovered flights. We did not increase the vacation penalty beyond

6000 because either the gaps or the uncovered flights increased when we increased it from 5000 to 6000. The final solutions are found in a reasonable time. In practice, if the integrality gap is greater than 1%, it is advisable to use the solution of the penultimate iteration or to apply different branching strategies.

Tableau 5.2 $I1-727$- Variations of Vacation Penalty

| | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vacation penalty | 1000 | | 2000 | | 3000 | | 4000 | | 5000 | | 6000 | |
| Preferred flight bonus | -50 | | -50 | | -50 | | -50 | | -50 | | -50 | |
| Pairing similarity (%) | 98.26 | | 98.84 | | 97.67 | | 98.84 | | 98.84 | | 98.84 | |
| Duty similarity (%) | 99.44 | | 99.63 | | 99.26 | | 99.63 | | 99.63 | | 99.63 | |
| Total no. of CG iterations | 1103 | 969 | 815 | 925 | 740 | 1637 | 644 | 985 | 830 | 721 | 1066 | 701 |
| Total CPU time (min) | 3.75 | 3.21 | 2.76 | 3.02 | 2.38 | 1.38 | 2.14 | 3.22 | 2.93 | 2.35 | 3.54 | 2.24 |
| Gap (%) | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 1.72 | 0.00 | 0.01 | 0.01 | 0.00 | 0.73 | 0.01 |
| Uncovered flights (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.99 | 0.99 | 0.00 | 0.00 | 0.00 | 0.00 | 1.18 | 1.18 |
| Preferred flights (%) | 24.68 | 24.38 | 26.65 | 24.68 | 26.75 | 23.49 | 26.46 | 23.69 | 26.55 | 25.07 | 26.67 | 24.58 |
| Satisfied vacation preferences (%) | 20.00 | 60.00 | 20.00 | 50.00 | 70.00 | 70.00 | 60.00 | 70.00 | 60.00 | 80.00 | 70.00 | 90.00 |

Tableau 5.3 $I2-DC9$- Variations of Vacation Penalty

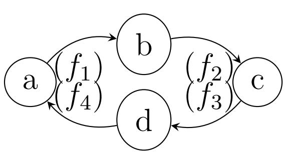
| | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vacation penalty | 1000 | | 2000 | | 3000 | | 4000 | | 5000 | | 6000 | |
| Preferred flight bonus | -50 | | -50 | | -50 | | -50 | | -50 | | -50 | |
| Pairing similarity (%) | 100 | | 99.67 | | 100 | | 100 | | 99.67 | | 100 | |
| Duty similarity (%) | 100 | | 99.86 | | 100 | | 100 | | 99.86 | | 100 | |
| Total no. of CG iterations | 2622 | 2527 | 2520 | 2670 | 2678 | 2621 | 2476 | 2273 | 2688 | 2538 | 2058 | 2786 |
| Total CPU time (min) | 14.06 | 14.45 | 15.20 | 15.11 | 16.49 | 9.24 | 15.20 | 12.60 | 16.77 | 14.51 | 12.24 | 16.37 |
| Gap (%) | 0.06 | 0.11 | 0.02 | 0.02 | 1.17 | 1.02 | 0.43 | 0.03 | 0.03 | 0.84 | 0.31 | 0.85 |
| Uncovered flights (%) | 0.00 | 0.40 | 0.00 | 0.00 | 0.40 | 0.53 | 0.93 | 0.93 | 0.00 | 0.40 | 0.40 | 0.53 |
| Preferred flights (%) | 26.53 | 26.13 | 26.73 | 26.60 | 26.71 | 26.41 | 26.11 | 25.84 | 26.00 | 26.07 | 26.40 | 25.77 |
| Satisfied vacation preferences (%) | 72.73 | 60.00 | 81.82 | 63.64 | 81.82 | 63.64 | 90.91 | 90.91 | 90.91 | 90.91 | 90.91 | 90.91 |

In the second group of tests we fix the vacation penalty at 5000, and the bonus for preferred flights varies between $-10$ and $-60$. The results for the three instances are given in Tables 5.5, 5.6, and 5.7 ; the information presented is the same as that in the earlier tables. We do not consider very low bonuses for covering preferred flights simply because the bonus is expressed as a negative cost, and this cost interacts with the real cost of the pairings. Preliminary results show that very low negative costs can result in a high percentage of uncovered flights. The results show that the algorithm is not very sensitive to the bonus for preferred flights. As mentioned, we did not have access to real data on employees' preferences, and these preferences are created by the random generators explained in detail in Kasirzadeh et al. (2015) ; the generators do not take into account correlations between the choices of preferred flights. It is difficult to determine the likely correlations, as the following example shows.

Tableau 5.4 $I3-D94$- Variations of Vacation Penalty

| | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vacation penalty | 1000 | | 2000 | | 3000 | | 4000 | | 5000 | | 6000 | |
| Preferred flight bonus | -50 | | -50 | | -50 | | -50 | | -50 | | -50 | |
| Pairing similarity (%) | 98.91 | | 99.27 | | 99.27 | | 99.27 | | 98.91 | | 98.54 | |
| Duty similarity (%) | 99.46 | | 99.73 | | 99.73 | | 99.60 | | 99.46 | | 99.46 | |
| Total no. of CG iterations | 2226 | 2530 | 2414 | 2490 | 2918 | 2838 | 3018 | 2430 | 2107 | 2417 | 2916 | 2672 |
| Total CPU time (min) | 43.91 | 54.55 | 48.33 | 51.14 | 60.77 | 63.90 | 67.53 | 51.32 | 38.71 | 50.37 | 66.16 | 58.01 |
| Gap (%) | 0.04 | 0.02 | 0.74 | 0.44 | 0.39 | 0.03 | 0.13 | 1.01 | 0.01 | 0.52 | 1.01 | 0.03 |
| Uncovered flights (%) | 0.22 | 0.22 | 0.81 | 0.81 | 1.51 | 1.51 | 0.59 | 0.92 | 0.70 | 0.70 | 1.02 | 1.02 |
| Preferred flights (%) | 25.78 | 25.78 | 26.16 | 25.94 | 26.07 | 25.52 | 24.36 | 22.97 | 25.96 | 26.89 | 24.74 | 26.32 |
| Satisfied vacation preferences (%) | 45.45 | 53.33 | 60.00 | 60.00 | 80.00 | 73.33 | 86.67 | 73.33 | 86.67 | 80.00 | 86.67 | 73.33 |

Consider a pairing composed of one duty that includes four flights between airports (a), (b), (c), and (d). If the pilot prefers ($f_2$), he/she may also choose as preferred flights ($f_1$) and a return path to base (a) that contains ($f_3$) and ($f_4$). He/she can also choose another combination of flights that can be included in a good pairing. These choices make it possible to assign the four preferred flights in a duty of four flights. However, we generate each employee's preferred flights by randomly choosing 10% of the flights from the set of pairings associated with his/her base. Therefore, it is difficult to have more than one or two preferred flights from a pairing. On average, there are five to seven flights per pairing, so the percentage of preferred flights is unlikely to be above 25%.




To improve the percentage of preferred flights, we need access to an expert who knows aircraft routing, and we do not have such access. In addition, we use a stopping criterion to reduce the computational time. The search for the optimal solution therefore does not explore all the possibilities.

We did not explore scheduling for medium-haul aircraft. Our preliminary results show that the computational times are excessive (more than one day for one iteration of an instance with 5613 scheduled flights and 145 pilots and copilots).

To compare the integrated and sequential approaches, we solved a personalized assignment problem for each of the pilots and copilots. The integrated approach gives better results in terms of the satisfaction of the flight and vacation preferences. For the vacations, see Figures 5.3 and 5.4 ; the percentage of preferences satisfied is the average over all three instances. The improvement is 5.25% for pilots and 4.14% for copilots when the flight bonus

Tableau 5.5 $I1-727$- Variations of Preferred Flight Bonus

| | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vacation penalty | 5000 | | 5000 | | 5000 | | 5000 | | 5000 | | 5000 | |
| Preferred flight bonus | -10 | | -20 | | -30 | | -40 | | -50 | | -60 | |
| Pairing similarity (%) | 98.84 | | 98.26 | | 98.84 | | 98.84 | | 98.84 | | 98.84 | |
| Duty similarity (%) | 99.63 | | 99.44 | | 99.63 | | 99.63 | | 99.63 | | 99.63 | |
| Total no. of CG iterations | 832 | 550 | 754 | 1283 | 641 | 1056 | 596 | 738 | 830 | 721 | 474 | 834 |
| Total CPU time (min) | 2.76 | 1.82 | 2.52 | 4.28 | 2.15 | 3.59 | 2.09 | 2.46 | 2.93 | 2.35 | 1.73 | 2.79 |
| Gap (%) | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 | 0.03 |
| Uncovered flights (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Preferred flights (%) | 26.60 | 24.58 | 26.65 | 24.58 | 26.75 | 24.58 | 26.46 | 24.68 | 26.55 | 25.07 | 26.75 | 24.98 |
| Satisfied vacation preferences (%) | 60.00 | 80.00 | 60.00 | 80.00 | 60.00 | 80.00 | 60.00 | 80.00 | 60.00 | 80.00 | 60.00 | 80.00 |

Tableau 5.6 $I2-DC9$- Variations of Preferred Flight Bonus

| | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vacation penalty | 5000 | | 5000 | | 5000 | | 5000 | | 5000 | | 5000 | |
| Preferred flight bonus | -10 | | -20 | | -30 | | -40 | | -50 | | -60 | |
| Pairing similarity (%) | 100 | | 99.34 | | 99.34 | | 99.67 | | 99.67 | | 99.34 | |
| Duty similarity (%) | 100 | | 99.59 | | 99.59 | | 99.86 | | 99.86 | | 99.59 | |
| Total no. of CG iterations | 2691 | 2774 | 2963 | 2650 | 2749 | 2551 | 2322 | 2836 | 2688 | 2538 | 2261 | 2373 |
| Total CPU time (min) | 16.20 | 16.26 | 18.59 | 15.58 | 17.38 | 14.89 | 14.13 | 17.13 | 16.77 | 14.51 | 13.12 | 13.80 |
| Gap (%) | 0.02 | 0.02 | 0.01 | 0.01 | 0.02 | 0.08 | 1.11 | 0.07 | 0.03 | 0.84 | 0.00 | 0.01 |
| Uncovered flights (%) | 1.13 | 1.13 | 1.07 | 1.07 | 0.13 | 0.13 | 0.27 | 0.27 | 0.00 | 0.40 | 1.80 | 1.80 |
| Preferred flights (%) | 26.84 | 24.81 | 26.28 | 26.08 | 26.10 | 25.17 | 26.54 | 25.07 | 26.00 | 26.07 | 26.82 | 26.41 |
| Satisfied vacation preferences (%) | 90.91 | 90.91 | 90.91 | 90.91 | 90.91 | 90.91 | 81.82 | 90.91 | 90.91 | 90.91 | 90.91 | 90.91 |

Tableau 5.7 $I3-D94$- Variations of Preferred Flight Bonus

| | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots | Pilots | Co-pilots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vacation penalty | 5000 | | 5000 | | 5000 | | 5000 | | 5000 | | 5000 | |
| Preferred flight bonus | -10 | | -20 | | -30 | | -40 | | -50 | | -60 | |
| Pairing similarity (%) | 98.54 | | 97.81 | | 98.18 | | 98.91 | | 98.91 | | 98.91 | |
| Duty similarity (%) | 99.46 | | 98.93 | | 99.20 | | 99.60 | | 99.46 | | 99.60 | |
| Total no. of CG iterations | 3259 | 2726 | 3108 | 2976 | 2185 | 2602 | 3049 | 3138 | 2107 | 2417 | 2374 | 2683 |
| Total CPU time (min) | 73.14 | 62.54 | 68.06 | 48.29 | 46.63 | 55.86 | 64.38 | 69.63 | 38.71 | 50.37 | 46.93 | 56.64 |
| Gap (%) | 0.08 | 0.21 | 0.91 | 0.47 | 0.01 | 0.01 | 0.08 | 0.07 | 0.01 | 0.52 | 0.52 | 2.16 |
| Uncovered flights (%) | 0.43 | 0.49 | 0.86 | 0.86 | 0.97 | 0.97 | 0.92 | 0.92 | 0.70 | 0.70 | 1.51 | 1.51 |
| Preferred flights (%) | 24.92 | 26.07 | 24.97 | 25.24 | 26.42 | 25.87 | 25.97 | 25.97 | 25.96 | 26.89 | 25.85 | 25.41 |
| Satisfied vacation preferences (%) | 86.67 | 73.33 | 86.67 | 73.33 | 86.67 | 73.33 | 86.67 | 73.33 | 86.67 | 80.00 | 86.67 | 73.33 |

is -50 and the vacation penalty is 5000. We do not present an equivalent figure for the preferred flights because the improvement is small (less than 3% on average).

To evaluate the efficiency of performing several iterations in the heuristic algorithm, we compare the average number of differing pairings and duties over all the tests ; see Figures 5.5 and 5.6. The results show that allowing several iterations leads to more robust schedules. Over the three iterations the number of pairings decreases by 2.38, 1.25, and 4.88 for instances $I1-727$, $I2-DC9$, and $I3-D94$, and the number of duties decreases by 3.67, 2.00, and 6.32.

For larger instances with 5000–7000 flights and 145–305 crew members, the size of the master problem increases. The numbers of subproblems, CG iterations, and branching nodes also increase. With appropriate strategies such as limits on the number of subproblems during the process, it will be possible to apply the heuristic algorithm to larger problems.

### 5.6 Conclusion

We have proposed a set partitioning formulation and a heuristic algorithm for the integrated personalized cockpit crew scheduling problem, which has not yet been investigated in the literature. Taking the crew preferences into account is common in European airlines and increasingly adopted in North America. We considered preferred flights and vacations. Our results show that the integrated approach satisfies more preferences than the sequential approach does. Furthermore, because of the inevitable perturbations, crew schedules need to be robust, and the integrated approach helps to provide more robust schedules by increasing the number of common pairings for pilots and copilots.

### 5.7 Acknowledgements

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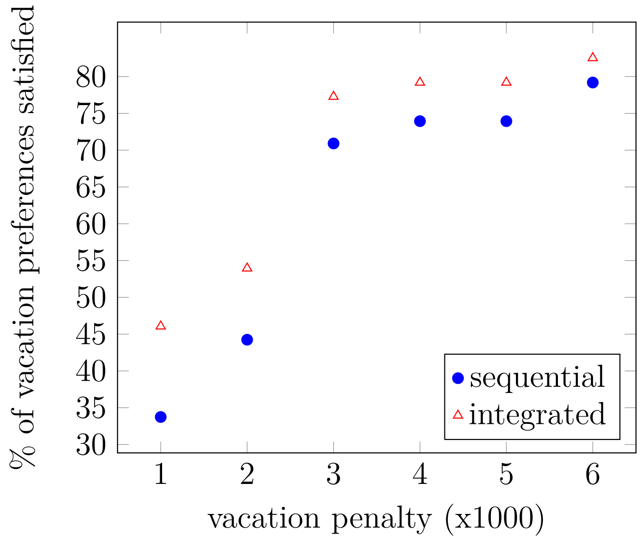


Figure 5.3 Sequential versus Integrated- Pilots

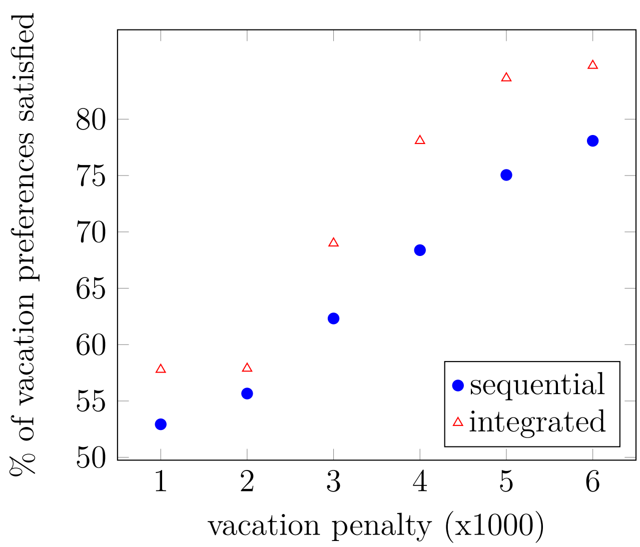


Figure 5.4 Sequential versus Integrated- Copilots

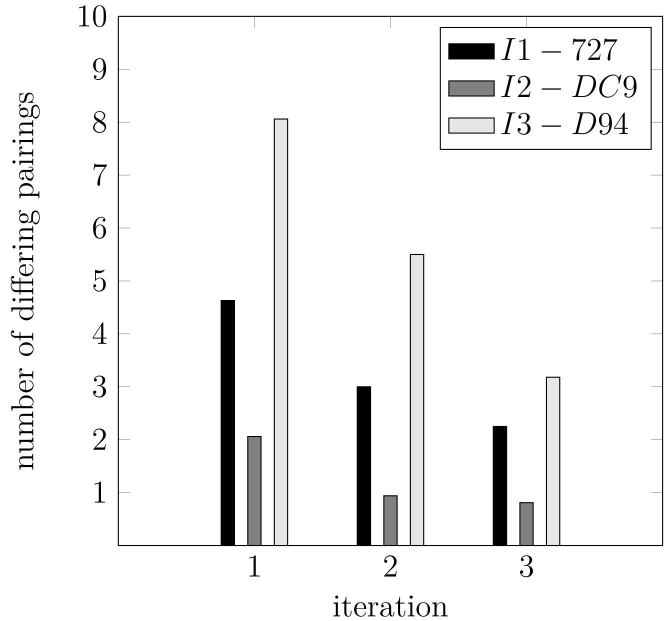


Figure 5.5 Differing pairings

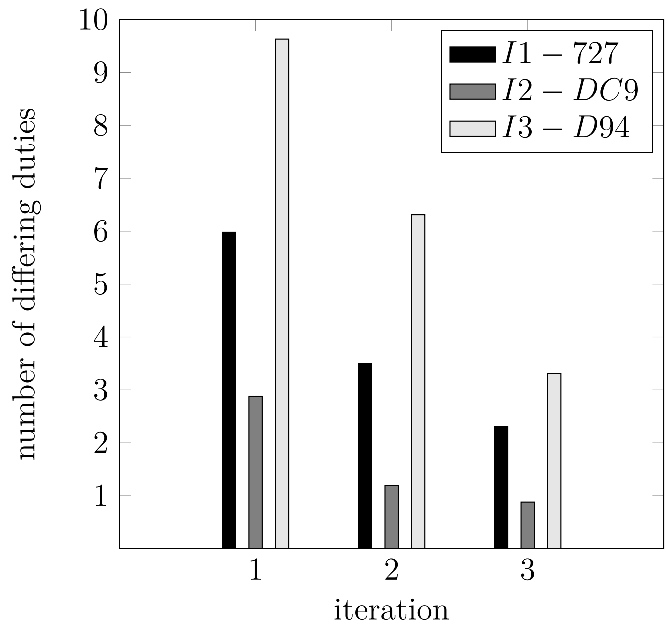


Figure 5.6 Differing duties

# CHAPITRE 6 ARTICLE 3 : SIMULTANEOUS OPTIMIZATION OF PERSONALIZED INTEGRATED RECOVERY FOR PILOTS AND COPILOTS

A. Kasirzadeh, F. Soumis, F. Lessard, M. Saddoune (2015), Simultaneous Optimization of Personalized Integrated Recovery for Pilots and Copilots. *Transportation Science*, soumis le 21 juin 2015.

**Abstract**

Various disturbances such as adverse weather conditions may result in delayed or canceled flights and affect the optimized schedules planned for airline crew members. In this paper, we solve the recovery problem via an integrated approach to reoptimize both the pairings and the personalized monthly plans. We solve this problem simultaneously for the pilots and copilots to obtain robust schedules that have the same pairings for pilots and copilots when possible. We propose a set partitioning formulation and we use column generation. We present results for seven instances from a major US carrier.

## 6.1 Introduction

Because of its complexity, the airline decision-making procedure is usually divided into *planning* and *recovery* stages (; Belobaba et al., 2012). The planning stage is frequently further subdivided into *flight scheduling*, *fleet assignment*, *aircraft maintenance and routing*, and *crew scheduling* (Kasirzadeh et al., 2015). Crew scheduling is then separated into *crew pairing* and *crew assignment* (; Gopalakrishnan and Johnson, 2005; Kasirzadeh et al., 2015). The crew pairing problem builds a minimum-cost set of pairings based on the scheduled flights such that the collective agreements and rules are respected. A *pairing* is a sequence of duties and overnight stops that starts and ends at a crew base. A *duty* is a sequence of flights (and/or deadheads) that forms a working day for a crew member ; the duties are separated by overnight stops. Each crew member is associated with a *base* located at a large airport. A *monthly schedule* is a sequence of pairings separated by time off. The crew assignment problem combines the pairings, vacations, preassigned activities, and rest periods to build a set of monthly schedules that respect the regulations and the collective agreement. The assignment procedure is either *bidline* or *personalized*. In the bidline approach, anonymous monthly schedules are constructed and assigned to crew members. Personalized assignment is either a *rostering* or *seniority-based* procedure. The rostering approach aims to maximize the global satisfaction, whereas the seniority-based approach maximizes the satisfaction of the crew members in seniority order. Traditionally, the crew pairing and crew assignment problems have been solved sequentially ; more recently, some researchers have integrated the two steps.

On the day of operation, external and/or internal perturbations may occur. These perturbations include late or absent crew members, aircraft breakdowns and unscheduled maintenance, security delays, air traffic control adjustments for meteorological reasons, and severe weather patterns such as snow storms. These disruptions result in delayed or canceled flights. Data from the Bureau of Transportation Statistics show that from 2005 to 2013 on average 20.39% of scheduled flights were delayed and 1.91% were canceled. Delayed and canceled flights directly affect the crew schedules, and adjustments become necessary. The recovery procedure is complex because it includes fleet reassignment and maintenance recovery, crew pairing and monthly schedule recovery, and passenger-itinerary recovery. These steps are often solved sequentially : first the flights are rescheduled, then the aircraft are rerouted, the crew schedules are updated, and the itineraries are adjusted. This traditional approach is presented in Figure 1.

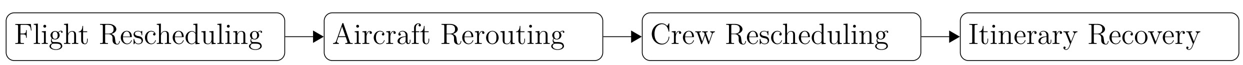


Figure 6.1 Schematic of Sequential Airline Recovery Procedure

In this paper, we focus on the crew rescheduling (recovery) problem, because the cost of the crew members is the second largest cost for airlines (after fuel). The algorithms for the crew recovery problem are similar to those applied for planning purposes. However, there are five major differences between the crew recovery and crew planning problems. First, the crew recovery problem cannot be separated into pairing and assignment steps. The updated pairings have to fit into the monthly schedules, so it is necessary to integrate the construction of new pairings and the adjustment of the monthly schedules. Second, the pilots and copilots must be treated simultaneously. The pairings should be the same for pilots and copilots, when possible, to maintain the robustness of the solution. When they are not the same, one flight perturbation will affect two different pairings, which will then affect more flights, and so the perturbation propagates through the monthly schedule. Third, the crew recovery problem must be solved quickly, whereas the crew planning problem is solved several weeks prior to operation. Fourth, the crew planning problem has a planning horizon that is frequently one month, whereas crew recovery reoptimizes the schedules locally for a period of a few days; therefore, the dimension of the optimization problem is reduced. Fifth, the objectives of crew planning are usually cost minimization and efficient crew utilization, whereas crew recovery has several conflicting objectives. These include minimizing the crew delays and minimizing the cost of the recovery operations.

The recovery problem must be small enough to be solved in a reasonable time, but its reoptimization domain must be sufficiently large to permit us to find feasible schedules for the rescheduled tasks. The main concern is to cover, in the most cost-efficient way, the set of flights while remaining as close as possible to the original schedules. It is important to minimize the number of flights that cannot be operated due to lack of sufficient crew. Crew recovery may involve rescheduling crew or deploying reserve crew members.

The contribution of this paper is an optimization approach for the integrated recovery of pairings and schedules for pilots and copilots simultaneously. This integrated approach considers both the pairing reoptimization and the recovery of monthly crew schedules, given all the relevant regulations. The problem is solved for pilots and copilots simultaneously to provide more robust schedules that reduce the propagation of perturbations. The rescheduled flights are input data. To the best of our knowledge, this paper presents the first mathematical programming method for the simultaneous recovery problem for pilots and copilots. Our main contribution is to demonstrate that a mathematical programming method can solve the personalized recovery problem for instances with up to 610 pilots and copilots in a reasonable time. We use column generation (CG).

The remainder of this paper is organized as follows. In Section 6.2, we provide a comprehensive literature review of crew recovery. Section 6.3 provides a detailed description of the problem, and Section 6.4 gives the mathematical formulation. Section 6.5 explains our algorithm, Section 6.6 gives our results, and Section 6.7 provides concluding remarks.

## 6.2 Literature Review

Short computational times are required for airline recovery optimization, so the optimization problem must be small. We can either consider fewer crew members or restrict the time span of the reoptimization window.

To the best of our knowledge, the first survey of irregular airline operations is that by Clarke (1998). He gives an extensive overview of the operations control center with respect to irregularities. He presents decision-support systems and algorithms based on operational data from the US domestic market. Filar et al. (2001) and Kohl et al. (2007) survey the state-of-the-art of decision-making for the airline recovery problem. They report on their research and development for large-scale airline disruption management. Another survey of the management of disruption in the airline industry is provided by Clausen et al. (2010). They also report a comparative study of aircraft/crew planning and recovery to explore the similarities between the solution approaches. Barnhart and Smith (2012) provide an overview of the role of OR in improving airline efficiency at the operational level.

Research on this topic began with investigations of aircraft scheduling in the presence of irregular operations (Clausen et al., 2010). This is a less complex problem : there are fewer aircraft than crew members and the aircraft rules are simpler than the crew-scheduling regulations. Teodorović and Guberinić (1984), Teodorović and Stojković (1990), Jarrah et al. (1993), Rakshit et al. (1996), Mathaisel (1996), Talluri (1996), Yan and Yang (1996), Clarke (1997), Clarke and Laporte (1997), Yan and Tu (1997), Cao and Kanafani (1997a), Cao and Kanafani (1997b), Luo and Yu (1997), Argüello et al. (1997), Luo and Yu (1998), Thengvall et al. (2000), Thengvall et al. (2001), Thengvall et al. (2003), Bard et al. (2001), Rosenberger et al. (2003), Andersson and Värbrand (2004), Andersson (2006), Liu et al. (2008), Eggenberg et al. (2007), and Zhao and Zhu (2007) studied aircraft recovery. We do not review this literature because the problem is not the focus of this paper.

There are three versions of the crew recovery problem. The first assumes that the flight schedules have already been recovered, i.e., the recovered flight schedules are input data for the crew recovery problem. Wei et al. (1997) and Song et al. (1998) provide a generalized set covering formulation for the crew pairing repair problem with reserve crew members. The objective is to repair the disturbed pairings as soon as possible while minimizing the cost. The branch and bound heuristic gives good results for small instances. Stojković et al. (1998) propose a set partitioning formulation for the operational crew scheduling problem and apply CG. They minimize the cost of covering all the flights with available crew members and minimize the crew disturbances. They allow only one modified pairing per crew member. To find the new pairings, they solve the crew pairing and the personalized monthly assignment problems simultaneously. They report results for small instances (with up to 32 crews and 210 flights) over one-day and seven-day periods. Medard and Sawhney (2007) expand the framework of Stojković et al. (1998) by permitting more than one modified pairing for each of the disrupted crew schedules. They propose an integrated pairing and assignment set covering problem in which the rescheduled flights replace the pairings. They solve the rescheduling problem by CG and provide results for small and medium instances. Nissen and Haase (2006) present a set covering formulation and a branch-and-price approach for the duty-period-based recovery problem for European airlines. They use CG and report results for small instances. Guo (2005) formulates the recovery problem as a set partitioning problem with the objective of minimizing the modifications to the planned schedule. CG and a genetic algorithm are used to find a balance between solution quality and computational time.

The second version of the problem allows flight cancellations. Johnson et al. (1994) present a set covering formulation. They take into account pairing and deadheading costs while forcing crew members to retain the same bases in the new solution. Results are presented for small instances. Lettovsky et al. (2000) present a set covering formulation. They use a fast pairing generator and a branch and price technique, successfully handling small to medium disruptions. The pairing generation is designed to minimize the modifications to the original schedule. Yu et al. (2003) discuss the implementation of a crew recovery decision support system at Continental Airlines ; it is a refined version of the model of Wei et al. (1997). They report good results and short computational times for small and medium instances.

The third version of the problem allows flight departures to be delayed. Stojković and Soumis (2001) extend the work of Stojković et al. (1998), presenting a set covering model and a CG approach. Reserve crew members are also allowed. They present results for instances with up to 59 pilots with 52 flights out of 190 being delayed. Stojković and Soumis (2005) extend this work. They simultaneously optimize the modifications to the flight departure times and the individual duties. The objective is to cover the maximum number of flights and to minimize the modifications to both the flights and the duties. Results for medium instances are reported. Abdelghany et al. (2004) provide a crew recovery decision support system for commercial hub-and-spoke airlines ; they present good results for medium instances.

Since 1997 researchers have tried to integrate the different steps of the airline recovery problem. Lettovsky (1997) presents an integrated approach for aircraft, crew, and passenger recovery and proposes an algorithm based on Benders decomposition. Bratu and Barnhart (2006) solve the passenger recovery problem while limiting the scheduling costs resulting from the perturbations. They permit delayed or canceled flights, and they make use of spare aircraft and reserve crew members. Zhang and Hansen (2008) present a model for a hub-and-spoke network that uses various modes of transportation to accommodate passengers whose travel plans have been perturbed. Abdelghany et al. (2008) present a commercial integrated approach to recovery when flights are delayed by severe weather conditions. Simultaneous recovery for aircraft and passengers is explored by Bisaillon et al. (2011) and Jafari and Zegordi (2011). Petersen et al. (2012) present a mathematical model and CG-based algorithm for the integrated flight, aircraft, crew, and passenger recovery problem. They give results for the hub-and-spoke network of a US carrier. Zhang and Lau (2014) present a set partitioning formulation for integrated flight, aircraft, and crew recovery. They provide a rolling-horizon algorithm and give results for small and medium instances from a US carrier.

## 6.3 Problem Description

The goal of crew recovery is to quickly produce good solutions that cover the perturbed flights. Compared to the planning problem, crew recovery is more localized, focusing on the components that are affected by disturbances. Although only small portions of the crew schedules are affected, all the rules and regulations must continue to be satisfied for the full month. It is important to keep pilot-copilot pairs together in the new duties and pairings ; this helps to ensure more robust schedules. Figure 2 shows the reoptimization window to illustrate the reduced size of the crew recovery problem.

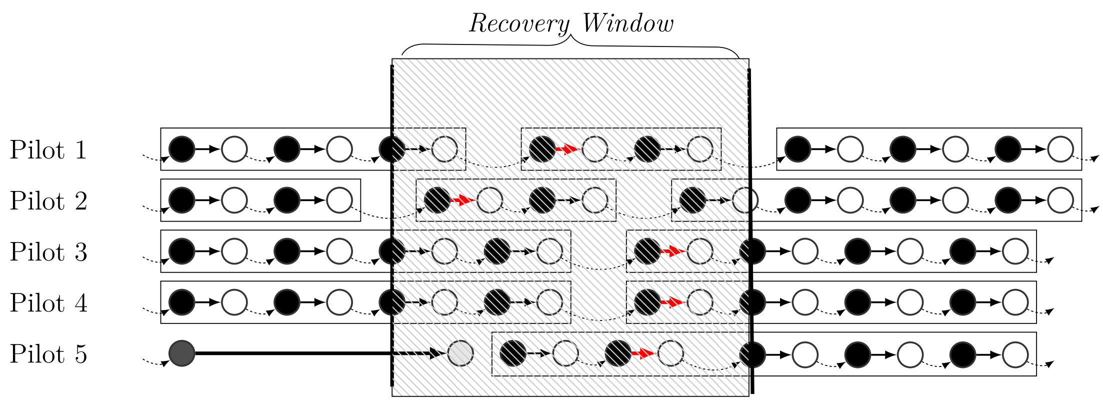


Figure 6.2 Reduced Size of Crew Recovery Problem

Our primary goals for the simultaneous optimization of the pilot and copilot recovery problems are : (1) recovering the pairings and monthly schedules together, (2) recovering the pairings and monthly schedules for pilots and copilots simultaneously, and (3) solving the recovery problem quickly. We propose a heuristic that iterates between the *pilot recovery problem (PRP)* and *copilot recovery problem (CRP)*. At each iteration, the PRP or the CRP is solved using CG. The objective is to cover all the flights (perturbed and unperturbed) that lie within the reoptimization window while satisfying the preferences of the pilots and copilots, if possible. The algorithm starts from a set of monthly schedules for the pilots. In the first step, it takes the perturbed flights into account and solves the PRP over the reoptimization window. The set of pairings that lies within the recovery window is updated accordingly. This set of reoptimized pairings will fit within the monthly schedules for the pilots and copilots. In the second step, given this new set of pairings and the initial monthly schedules for the copilots, we solve the CRP. Using the new pairings obtained, we solve the PRP again and so on. This process continues until a stopping criterion is satisfied. We use a stopping criterion (a maximum number of iterations) because it may take a long time for the algorithm to converge. The algorithm is illustrated in Figure 3.

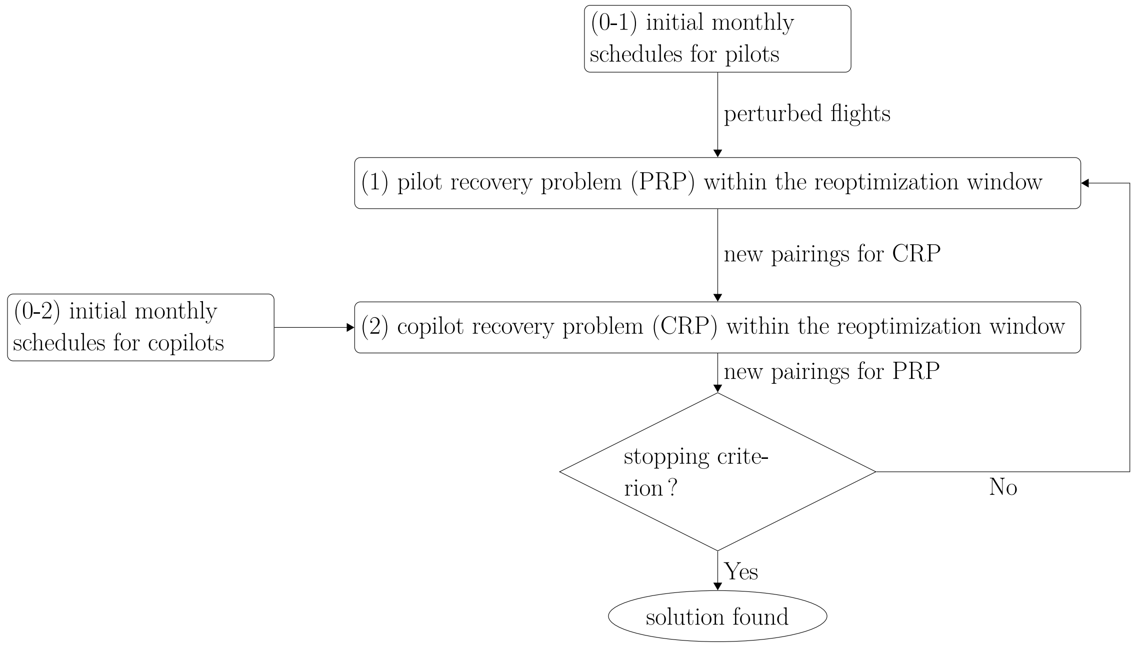


Figure 6.3 Heuristic algorithm for integrated crew recovery problem

## 6.4 Mathematical Formulation

The simultaneous cockpit crew recovery problem is mathematically formulated using the following notation :

**Sets**

$F_n$ : set of unperturbed flights in recovery window ;

$F_r$ : set of rescheduled flights ;

$P_r$ : set of feasible pairings overlapping recovery window ;

$L$ : set of pilots ;

$V_{l,r}$ : set of vacation preferences for pilot $l \in L$ in recovery window ;

$G_{l,r}$ : set of preferred flights for pilot $l \in L$ in recovery window ;

$S_l$ : set of feasible schedules for pilot $l \in L$ ;

**Parameters**

$C_{s,l}^{recovery}$ : cost of personalized schedule $s \in S_l$ for pilot $l \in L$ during recovery window ;

$\bar{C}_f$ : penalty for not covering flight $f \in F_n \cup F_r$ ;

$C_p$ : cost of feasible pairing $p \in P_r$ ;

$n^l_{s,r}$ : number of preferred flights in recovery window in schedule $s \in S_l$ for pilot $l \in L$ ;

$c^l_{f,r}$ : bonus for covering preferred flight $f \in G_{l,r}$ for pilot $l \in L$ ;

$c^l_v$ : penalty for not covering vacation preference $v \in V_l$ ;

$$e^{s,l}_f = \begin{cases} 1 & \text{if flight } f \in F_n \cup F_r \text{ is covered by pilot } l \in L \text{ in schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

$$e^{s,l}_p = \begin{cases} 1 & \text{if pairing } p \in P_r \text{ is covered by pilot } l \in L \text{ in schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

$$v^{s,l}_v = \begin{cases} 1 & \text{if vacation } v \in V_{l,r} \text{ is covered by schedule } s \in S_l \\ 0 & \text{otherwise}\,; \end{cases}$$

**Variables**

$$x^s_l = \begin{cases} 1 & \text{if schedule } s \in S_l \text{ for pilot } l \in L \text{ is chosen} \\ 0 & \text{otherwise}\,; \end{cases}$$

$$\bar{e}_f = \begin{cases} 1 & \text{if flight } f \in F_n \cup F_r \text{ is not covered} \\ 0 & \text{otherwise.} \end{cases}$$

The recovery formulation for $PRP$ is :

$$\sum_{l \in L} \sum_{s \in S_l} C^{recovery}_{s,l} x^s_l + \sum_{f \in F_n \cup F_r} \bar{e}_f \bar{C}_f \tag{6.1}$$

$$\text{s.t.} \sum_{l \in L} \sum_{s \in S_l} e^{s,l}_f x^s_l + \bar{e}_f = 1, \qquad \forall f \in F_n \cup F_r \tag{6.2}$$

$$\sum_{s \in S_l} x^s_l \leq 1, \qquad \forall l \in L \tag{6.3}$$

$$x^s_l \in \{0, 1\}, \qquad \forall l \in L, \forall s \in S_l \tag{6.4}$$

The recovery formulation for $CRP$ is the same as (1)–(4) with the set of pilots ($L$) replaced by the set of copilots. The cost of the personalized schedule within the recovery window for pilot $l \in L$ is calculated via

$$C^{recovery}_{s,l} = \sum_{p \in P_r} e^{s,l}_p C_p + n^l_{s,r} c^l_{f,r} + \sum_{v \in V_{l,r}} (1 - v^{s,l}_v) c^l_v.$$

The objective (1) minimizes the total cost associated with the pilot schedules restricted to the recovery window. Constraints (2) ensure that perturbed and unperturbed flights within the reoptimization window are covered exactly once. Constraints (3) assign at most one schedule to each pilot, and constraints (4) are the binary requirements for the variables.

The schedule cost is composed of the pairing cost plus the penalties and bonuses for preferences. In practice, the pairing cost has a complex nonlinear structure, and an approximation is often used. To calculate the pairing cost, we use the cost function of Saddoune et al. (2013) that includes the deadhead, waiting, and duty costs. We take the preferences into account by introducing bonuses and penalties. Our preliminary results suggest a bonus of $-50$ for covering a preferred flight and a penalty of 5000 for not covering a vacation preference. The cost of not covering a scheduled flight is set to 10000 (all costs are in dollars). These values ensure that a good percentage of the preferences are satisfied while the gap remains small.

## 6.5 Algorithm

We use CG to solve the simultaneous personalized integrated recovery problem for pilots and copilots. CG is one of the most practical approaches for large-scale mixed integer problems ( ). The linear relaxation of the recovery problem (1)–(4) is called the master problem. At each iteration of CG, we consider a restricted master problem (RMP) that contains a subset of the columns (variables). We solve the RMP using a standard linear programming algorithm such as the simplex method. This gives an optimal objective-function value and a pair of primal and dual solutions. Given this optimal dual solution, the current subproblem tries to find columns with negative reduced costs. If such columns are found, they are added to the RMP for the next iteration. Each subproblem corresponds to a resource-constrained shortest path problem, and we solve it by dynamic programming. When no variable with a negative reduced cost can be found, the optimal solution for the RMP is optimal for the master problem. In practice, because of slow convergence, the CG is often stopped before optimality is reached. Two parameters determine the CG stopping criterion. We stop the CG if in the last $i$ iterations the objective value has decreased by less than a threshold $\alpha$. These values are selected based on preliminary tests : $i$ is set to 25 for instances 1–5 and to 10 for instances 6–7, and $\alpha$ is set to 0.001%. These choices greatly reduce the search domain for the optimization.

We can associate an acyclic network $G$, with node set $N$ and arc set $R$, with each employee. To solve the subproblems, we must find shortest paths within these networks with negative reduced costs that satisfy the resource constraints. We use dynamic programming. We use the network structure, resources, and label-setting algorithm of Kasirzadeh et al. (2014).

We use two branching strategies at each node of the branch and bound tree. The first strategy fixes all the fractional values greater than a predetermined threshold to 1 ; we set the threshold to 0.85. The second strategy forces two flights to be consecutive in a pairing. We choose the branching strategy for a given node by computing a score for each strategy and choosing the strategy with the higher score.

## 6.6 Computational Results

In this section, we present results for seven test instances. They are based on historical data for scheduled flights operated by short- and medium-haul aircraft in a major North American airline. The reoptimization is performed on monthly personalized schedules for pilots and copilots that are obtained by solving the personalized crew scheduling problem. For instances 1–3 (which are small), we find the monthly schedules by solving the simultaneous personalized integrated scheduling problems for pilots and copilots (Kasirzadeh et al., 2014). For the larger instances 4–7, we construct the personalized monthly schedules using the sequential approach presented by Kasirzadeh et al. (2015).

All the tests were executed on a Linux PC equipped with an Intel (R) Xeon (R) processor clocked at 2.93 GHz. The heuristic is coded in C++. We use the GENCOL column generation library (version 4.5) and the linear programming solver CPLEX 12.4.

We apply all the constraints used to construct personalized schedules for pilots and copilots at the planning level. Severe weather is the hypothetical disturbance that we consider. We construct four scenarios for disturbed flights. For each instance, we assume that the perturbations occur only in the largest base. The four scenarios are :

1. The perturbation occurs between 5 p.m. and 6 p.m. on the 15th of the month. It results in a delay of one hour for all the flights departing in this interval. The reoptimization window is from 4 p.m. on the 15th to 4 a.m. on the 16th.
2. This is identical to scenario 1 except that the perturbation results in a delay of two hours.
3. This perturbation affects 50% of the flights that arrive or depart between 4 p.m. and 6 p.m. on the 15th of the month. It results in a delay of two hours. The reoptimization window is from 1 p.m. on the 15th to 4 a.m. on the 16th.
4. This perturbation affects 50% of the flights that arrive or depart between 10 a.m. and 1 p.m. on the 15th of the month. It results in a delay of one hour. The reoptimization window is from 8 a.m. on the 15th to 4 a.m. on the 16th.

Tables 1–7 present the features of each reoptimization problem and the results for each perturbation scenario. The first five rows indicate the size of the reoptimization problem. The *no. of crew members* indicates the number of pilots and copilots with planned schedules. The *no. of active flights* is the number of flights within the recovery window. The *no. of active duties* and the *no. of active pairings* are the numbers of duties and pairings that overlap the reoptimization window and are included in the recovery problem. The *no. of delayed flights* is the number of delayed flights in the corresponding scenario.

Tableau 6.1 Results for Instance 1

| | Scenario 1 | | Scenario 2 | | Scenario 3 | | Scenario 4 | |
|---|---|---|---|---|---|---|---|---|
| | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots |
| No. of crew members | 33 | 33 | 33 | 33 | 33 | 33 | 33 | 33 |
| No. of active flights | 22 | | 22 | | 30 | | 34 | |
| No. of active duties | 12 | | 12 | | 13 | | 13 | |
| No. of active pairings | 12 | | 12 | | 13 | | 13 | |
| No. of delayed flights | 6 | | 6 | | 9 | | 5 | |
| Total no. of CG iterations | 70 | 73 | 78 | 84 | 75 | 84 | 111 | 99 |
| Total CPU time (s) | 1.50 | 1.20 | 1.70 | 1.20 | 1.60 | 1.30 | 2.40 | 1.50 |
| Gap (%) | 0.00 | 2.24 | 0.00 | 1.91 | 0.00 | 1.19 | 0.00 | 0.00 |
| Pairing similarity (%) | 100 | | 100 | | 76.92 | | 100 | |
| Duty similarity (%) | 100 | | 100 | | 76.92 | | 100 | |
| No. of uncovered flights | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| Loss of flight preferences (%) | -1.52 | 3.03 | -1.52 | -1.52 | 0.41 | 4.87 | 0.00 | 0.00 |
| Loss of vacation preferences (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cost increase (%) | 0.98 | 0.98 | 1.36 | 1.37 | -1.42 | 11.05 | 2.49 | 2.50 |

Tableau 6.2 Results for Instance 2

| | Scenario 1 | | Scenario 2 | | Scenario 3 | | Scenario 4 | |
|---|---|---|---|---|---|---|---|---|
| | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots |
| No. of crew members | 34 | 34 | 34 | 34 | 34 | 34 | 34 | 34 |
| No. of active flights | 31 | | 31 | | 44 | | 52 | |
| No. of active duties | 16 | | 16 | | 17 | | 18 | |
| No. of active pairings | 15 | | 15 | | 16 | | 17 | |
| No. of delayed flights | 5 | | 5 | | 4 | | 7 | |
| Total no. of CG iterations | 66 | 63 | 66 | 63 | 140 | 115 | 129 | 147 |
| Total CPU time (s) | 0.90 | 0.90 | 0.90 | 0.90 | 3.00 | 2.20 | 3.00 | 4.20 |
| Gap (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.34 | 0.01 | 0.00 | 0.00 |
| Pairing similarity (%) | 80.00 | | 80.00 | | 100 | | 100 | |
| Duty similarity (%) | 81.25 | | 81.25 | | 100 | | 100 | |
| No. of uncovered flights | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Loss of flight preferences (%) | 2.82 | 2.90 | 3.23 | 2.89 | -0.59 | 0.33 | 0.08 | 0.04 |
| Loss of vacation preferences (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cost increase (%) | 4.25 | 4.31 | 4.71 | 4.92 | 2.21 | 2.23 | 3.31 | 0.04 |

Tableau 6.3 Results for Instance 3

| | Scenario 1 | | Scenario 2 | | Scenario 3 | | Scenario 4 | |
|---|---|---|---|---|---|---|---|---|
| | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots |
| No. of crew members | 47 | 47 | 47 | 47 | 47 | 47 | 47 | 47 |
| No. of active flights | 41 | | 41 | | 51 | | 63 | |
| No. of active duties | 19 | | 18 | | 18 | | 22 | |
| No. of active pairings | 22 | | 21 | | 20 | | 24 | |
| No. of delayed flights | 6 | | 6 | | 4 | | 10 | |
| Total no. of CG iterations | 114 | 88 | 87 | 72 | 122 | 205 | 121 | 126 |
| Total CPU time (s) | 7.00 | 7.20 | 6.60 | 5.40 | 8.50 | 17.01 | 10.5 | 13.80 |
| Gap (%) | 1.03 | 0.84 | 0.00 | 0.00 | 0.00 | 0.07 | 0.00 | 0.00 |
| Pairing similarity (%) | 95.45 | | 95.24 | | 85.00 | | 100 | |
| Duty similarity (%) | 94.74 | | 94.44 | | 83.33 | | 100 | |
| No. of uncovered flights | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Loss of flight preferences (%) | 5.88 | 0.60 | -0.08 | 1.96 | 4.48 | 3.24 | 3.04 | 5.54 |
| Loss of vacation preferences (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cost increase (%) | 0.14 | 5.43 | 6.51 | 2.56 | -1.88 | -3.02 | 0.04 | -0.04 |

Tableau 6.4 Results for Instance 4

| | Scenario 1 | | Scenario 2 | | Scenario 3 | | Scenario 4 | |
|---|---|---|---|---|---|---|---|---|
| | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots |
| No. of crew members | 145 | 145 | 145 | 145 | 145 | 145 | 145 | 145 |
| No. of active flights | 125 | | 125 | | 162 | | 188 | |
| No. of active duties | 55 | | 57 | | 55 | | 66 | |
| No. of active pairings | 55 | | 57 | | 54 | | 65 | |
| No. of delayed flights | 12 | | 12 | | 11 | | 9 | |
| Total no. of CG iterations | 193 | 212 | 309 | 256 | 370 | 277 | 306 | 263 |
| Total CPU time (min) | 36.62 | 41.21 | 39.58 | 39.98 | 42.81 | 41.46 | 45.92 | 50.01 |
| Gap (%) | 0.00 | 0.00 | 0.09 | 0.10 | 0.13 | 0.02 | 0.00 | 0.00 |
| Pairing similarity (%) | 87.27 | | 77.19 | | 77.78 | | 96.92 | |
| Duty similarity (%) | 90.91 | | 80.70 | | 78.18 | | 96.97 | |
| No. of uncovered flights | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Loss of flight preferences (%) | -4.30 | -1.48 | -5.16 | -2.18 | -1.81 | 1.49 | 1.70 | 0.93 |
| Loss of vacation preferences (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cost increase (%) | 5.43 | 2.21 | 4.91 | 1.89 | 2.38 | 0.27 | 1.02 | 1.14 |

Tableau 6.5 Results for Instance 5

| | Scenario 1 | | Scenario 2 | | Scenario 3 | | Scenario 4 | |
|---|---|---|---|---|---|---|---|---|
| | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots |
| No. of crew members | 247 | 247 | 247 | 247 | 247 | 247 | 247 | 247 |
| No. of active flights | 115 | | 115 | | 149 | | 182 | |
| No. of active duties | 88 | | 88 | | 96 | | 103 | |
| No. of active pairings | 89 | | 89 | | 96 | | 101 | |
| No. of delayed flights | 14 | | 14 | | 9 | | 7 | |
| Total no. of CG iterations | 168 | 153 | 145 | 144 | 192 | 180 | 231 | 234 |
| Total CPU time (min) | 11.43 | 11.21 | 8.35 | 8.24 | 11.71 | 11.30 | 12.92 | 14.60 |
| Gap (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 |
| Pairing similarity (%) | 85.39 | | 80.90 | | 82.29 | | 86.14 | |
| Duty similarity (%) | 96.59 | | 87.50 | | 96.88 | | 94.17 | |
| No. of uncovered flights | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Loss of flight preferences (%) | 0.00 | 4.99 | 0.00 | 5.07 | 0.00 | -6.52 | 0.00 | -8.64 |
| Loss of vacation preferences (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cost increase (%) | 0.26 | 0.53 | 1.55 | 0.58 | 1.47 | 3.90 | 2.66 | 4.51 |

Tableau 6.6 Results for Instance 6

| | Scenario 1 | | Scenario 2 | | Scenario 3 | | Scenario 4 | |
|---|---|---|---|---|---|---|---|---|
| | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots |
| No. of crew members | 223 | 223 | 223 | 223 | 223 | 223 | 223 | 223 |
| No. of active flights | 129 | | 129 | | 169 | | 197 | |
| No. of active duties | 77 | | 78 | | 82 | | 86 | |
| No. of active pairings | 77 | | 78 | | 80 | | 84 | |
| No. of delayed flights | 13 | | 13 | | 12 | | 8 | |
| Total no. of CG iterations | 181 | 192 | 258 | 240 | 212 | 231 | 262 | 270 |
| Total CPU time (min) | 6.25 | 7.99 | 9.11 | 9.84 | 6.74 | 8.50 | 9.45 | 11.43 |
| Gap (%) | 0.00 | 0.00 | 0.03 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| Pairing similarity (%) | 92.21 | | 92.31 | | 95.00 | | 95.24 | |
| Duty similarity (%) | 100 | | 100 | | 100 | | 100 | |
| No. of uncovered flights | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Loss of flight preferences (%) | -0.51 | -0.60 | -0.10 | -0.01 | -3.20 | -0.59 | -1.60 | -2.17 |
| Loss of vacation preferences (%) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Cost increase (%) | 4.95 | 4.92 | 5.87 | 5.84 | 2.86 | 2.85 | 2.14 | 1.15 |

Tableau 6.7 Results for Instance 7

| | Scenario 1 | | Scenario 2 | | Scenario 3 | | Scenario 4 | |
|---|---|---|---|---|---|---|---|---|
| | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots | Pilots | Copilots |
| No. of crew members | 305 | 305 | 305 | 305 | 305 | 305 | 305 | 305 |
| No. of active flights | 160 | | 160 | | 212 | | 253 | |
| No. of active duties | 113 | | 113 | | 121 | | 127 | |
| No. of active pairings | 115 | | 115 | | 122 | | 126 | |
| No. of delayed flights | 9 | | 9 | | 23 | | 12 | |
| Total no. of CG iterations | 209 | 212 | 217 | 220 | 277 | 265 | 321 | 324 |
| Total CPU time (min) | 19.76 | 18.33 | 22.37 | 18.90 | 27.16 | 22.63 | 32.94 | 30.45 |
| Gap (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Pairing similarity (%) | 93.91 | | 97.35 | | 89.34 | | 95.28 | |
| Duty similarity (%) | 97.35 | | 97.39 | | 92.56 | | 92.06 | |
| No. of uncovered flights | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Loss of flight preferences (%) | -4.40 | -3.37 | -4.40 | -3.37 | 5.53 | 4.18 | 5.14 | 6.02 |
| Loss of vacation preferences (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cost increase (%) | 4.14 | 1.71 | 4.24 | 1.81 | 4.21 | 1.48 | 3.89 | 1.83 |

We use three indicators to assess the algorithm : the *no. of CG iterations* indicates the total number of CG iterations for the three iterations of the heuristic. The *CPU time* (in seconds for instances 1–3 and minutes for instances 4–7) indicates the total CPU time for the three iterations. The *gap* is the percentage difference between the LP solution and the integer solution. All the instances are solved in a reasonable computational time. Except for instance 1 (the smallest instance), the gap is smaller than 1.03. In practice, for small instances that are not hard to solve, it is advisable to apply different branching strategies when the gap is greater than 1%.

We use six indicators to assess the solution quality. The *pairing similarity* is the percentage of common pairings for pilots and copilots within the recovery window at the final iteration of the reoptimization process. There are two ways to encourage common sets of duties and pairings. The first is to introduce *soft constraints* : penalties for duties and pairings that are different. The second is to introduce hard constraints ; this restricts the domain of exploration. In this study, we use soft constraints. Our preliminary results show that an acceptable level of similarity is achieved when we set the penalty to 300.

The *duty similarity* is the percentage of common duties for pilots and copilots in the reoptimization window at the final iteration of the heuristic. The *no. of uncovered flights* indicates the number of flights in the reoptimization window that are uncovered despite the penalty imposed. The *loss of flight preferences* is the percentage of flight preferences lost after the perturbation, and the *loss of vacation preferences* is the percentage of vacation preferences lost. Negative losses indicate that more preferences are satisfied. The *cost increase* is the percentage increase in the cost of the portion of the monthly schedules within the recovery window.

For the test instances, the pairing similarity varies between 76.92% and 100% (with an average of 90.61% over all the tests). The duty similarity ranges between 76.92% and 100% (with an average of 93.33% over all the tests). This is an acceptable level of common pairings in a reoptimization context. In practice, the associated penalty could be lower or higher, depending on the importance that the airline attaches to common pairings and duties. Except in some of the scenarios for instances 1 and 3, all the flights are covered. The bonus for preferred flights gives an acceptable cost increase for the pilots and copilots and an acceptable loss of flight preferences after the reoptimization process. The bonus could be lower or higher depending on the importance that the airline attaches to flight preferences. We cannot yet provide an analysis of how changes to the bonus will impact the cost of the schedules ; this is a complex situation. One direction for further research is a study of the relationship between the bonus and the costs of the schedules. In our tests, none of the vacation preferences are lost after the perturbation.

### 6.7 Summary and Conclusions

We have proposed a new set partitioning formulation and a new heuristic that solves the integrated personalized recovery problem for pilots and copilots simultaneously. Our results indicate that the reoptimization algorithm covers the perturbed flights with an acceptable cost increase and loss of flight preferences. It can solve instances with up to 610 pilots and copilots in a reasonable computational time.

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# CHAPITRE 7 DISCUSSIONS GÉNÉRALES ET CONCLUSION

Dans cette thèse, nous avons étudié le problème d'optimisation intégrée des rotations et des blocs mensuels personnalisés des pilotes et des copilotes. Au début, nous avons présenté une revue de littérature sur la construction des horaires d'équipage en transport aérien. Pour le problème séquentiel de construction des blocs mensuels personnalisés, nous avons présenté un modèle mathématique et une approche de résolution basés sur la génération de colonnes.

Nous avons construit des blocs mensuels personnalisés en associant un sous-problème avec chaque membre d'équipage. Lors de nos tests, le nombre de sous-problèmes varie entre 33 et 305. Dans le problème non-personnalisé pour le même ensemble de données, un sous-problème est associé à chaque base de l'équipage (pour un total de 3 sous-problèmes). Le problème de construction personnalisée des blocs mensuels est donc plus difficile que le problème non-personnalisé.

La construction des horaires d'équipage prenant en compte les préférences de l'équipage est commune dans les compagnies aériennes européennes et devient plus fréquent dans les compagnies aériennes nord-américaines. Nous avons considéré deux types de préférences, les vols préférés et les vacances préférées, dans le contexte de court et moyen courriers. Les résultats numériques montrent qu'un niveau acceptable de satisfaction des équipages peut être réalisé lorsque les blocs mensuels sont construits pour les pilotes par une approche séquentielle basée sur la programmation mathématique.

Nous avons observé que peu de chercheurs comparent leurs méthodes de résolution sur les mêmes données. Nous proposons un ensemble de jeux de données avec des générateurs de préférences disponible en ligne pour permettre de réaliser des comparaisons.

Nous avons ensuite étudié le problème de construction des rotations et des blocs mensuels personnalisés avec une approche intégrée. Dans ce cas, les préférences d'équipages et les contraintes se traduisent par des blocs mensuels différents pour les pilotes et les copilotes. Toutefois, afin de maintenir la robustesse des blocs des membres d'équipage en cas de perturbations au niveau opérationnel, les pilotes et les copilotes doivent avoir des rotations similaires lorsque cela est possible.

Pour atteindre cet objectif, on propose un nouvel algorithme heuristique qui résout le problème de planification intégrée pour les pilotes et les copilotes simultanément. Chaque problème est formulé comme un problème de partitionnement d'ensemble, et l'approche de solution est basée sur la génération de colonnes et l'agrégation de contraintes.

Des expériences numériques sont présentées pour trois instances avec un maximum de 1 854 vols et 94 pilotes et copilotes. Nos résultats montrent que l'approche intégrée satisfait davantage les préférences que l'approche séquentielle. De plus, en raison des perturbations inévitables, les blocs mensuels d'équipages doivent être robustes. L'approche intégrée permet de fournir des blocs mensuels plus robustes en augmentant le nombre de rotations communes pour les pilotes et les copilotes.

Pour les grandes instances comprenant entre 5000 et 7000 vols et de 145 à 305 membres d'équipage, la taille du problème maître augmente. Le nombre de sous-problèmes, le nombre d'itérations de la méthode de génération de colonnes et le nombre de nœuds de branchement augmentent également. Avec les stratégies actuelles, on ne peut pas fournir de résultats dans des temps raisonnables pour les instances plus grandes. Une direction possible pour la recherche future serait de trouver des stratégies appropriées tel que limiter le nombre de sous-problèmes à chaque itération de génération de colonnes au cours du processus. Ensuite, il serait possible d'appliquer l'algorithme heuristique pour des problèmes plus grands.

Des perturbations arrivent souvent pendant l'exécution des blocs mensuels déjà planifiés. Pour étudier le problème de réoptimisation des blocs mensuels pour les pilotes et les copilotes, nous avons proposé une formulation de partitionnement d'ensemble avec un algorithme heuristique afin de résoudre le problème intégré de réoptimisation des blocs mensuels personnalisé pour les pilotes et copilotes simultanément. Cette formulation ainsi que l'algorithme pour le problème de réoptimisation n'avaient pas encore été étudiés dans la littérature.

Nos résultats indiquent que l'algorithme de réoptimisation fonctionne de façon satisfaisante pour la couverture des vols perturbés et qu'un niveau acceptable d'augmentation des coûts et de satisfaction de vol préféré est atteint. Les expériences numériques pour les instances avec un maximum de 610 pilotes et copilotes montrent des temps de calcul rapides.

Les différentes compagnies aériennes ont un choix à faire entre le coût des blocs mensuels et le niveau de vols préférés accordés aux pilotes et copilotes. Pour ce faire elles doivent ajuster les paramètres associés au bonus pour la satisfaction des vols préférés.

À ce stade du développement de la recherche, nous ne pouvons pas encore fournir une relation bien documentée entre la variation des changements sur les préférences satisfaisantes et l'augmentation du coût des blocs mensuels. Des études sur plusieurs compagnies aériennes seront nécessaires pour connaître l'influence des caractéristiques des problèmes sur cette relation. Ceci est une situation très complexe.

Selon les paramètres que nous avons fixés pour les bonus et les coûts de construction des horaires pour les pilotes et les copilotes, le pourcentage d'augmentation des coûts et la perte de la satisfaction des vols préféré sont acceptables. Une direction possible pour poursuivre les recherches sur ce problème est d'étudier la relation entre les coûts de satisfaction des préférences et les coûts de construction des blocs mensuels.

## RÉFÉRENCES

A. Abdelghany, G. Ekollu, R. Narasimhan, et K. Abdelghany, “A proactive crew recovery decision support tool for commercial airlines during irregular operations”, *Annals of Operations Research*, vol. 127, no. 1-4, pp. 309–331, 2004.

K.-F. Abdelghany, A.-F. Abdelghany, et G. Ekollu, “An integrated decision support tool for airlines schedule recovery during irregular operations”, *European Journal of Operational Research*, vol. 185, no. 2, pp. 825–848, 2008.

H. Achour, M. Gamache, F. Soumis, et G. Desaulniers, “An exact solution approach for the preferential bidding system problem in the airline industry”, *Transportation Science*, vol. 41, no. 3, pp. 354–365, 2007.

S. AhmadBeygi, A. Cohn, et M. Weir, “An integer programming approach to generating airline crew pairings”, *Computers & Operations Research*, vol. 36, no. 4, pp. 1284–1298, 2009.

R. Anbil, E. Gelman, B. Patty, et R. Tanga, “Recent advances in crew-pairing optimization at american airlines”, *Interfaces*, vol. 21, no. 1, pp. 62–74, 1991.

R. Anbil, R. Tanga, et E. L. Johnson, “A global approach to crew-pairing optimization”, *IBM Systems Journal*, vol. 31, no. 1, pp. 71–78, 1992.

E. Andersson, E. Housos, N. Kohl, et D. Wedelin, *Operations Research in the airline industry.* Springer, US, 1998.

T. Andersson, “Solving the flight perturbation problem with meta heuristics”, *Journal of Heuristics*, vol. 12, no. 1-2, pp. 37–53, 2006.

T. Andersson et P. Värbrand, “The flight perturbation problem”, *Transportation Planning and Technology*, vol. 27, no. 2, pp. 91–117, 2004.

M. Argüello, J. Bard, et G. Yu, “Grasp for aircraft routing in response to groundings and delays”, *Journal of Combinatorial Optimization*, vol. 1, no. 3, pp. 211–228, 1997.

A. Azadeh, M. H. Farahani, H. Eivazy, S. Nazari-Shirkouhi, et G. Asadipour, “A hybrid meta-heuristic algorithm for optimization of crew scheduling”, *Applied Soft Computing*, vol. 13, no. 1, pp. 158–164, 2013.

J. Bard, G. Yu, et M. Argüello, "Optimizing aircraft routings in response to groundings and delays", *IIE Transactions*, vol. 33, no. 10, pp. 931–947, 2001.

C. Barnhart et B. C. Smith, *Quantitative Problem Solving Methods in the Airline Industry.* Springer, New York, 2012.

C. Barnhart, E. L. Johnson, R. Anbil, et L. Hatay, "A column-generation technique for the long-haul crew-assignment problem", dans *Optimization in industry 2.* John Wiley & Sons, Inc., 1994, pp. 7–24.

C. Barnhart, E. L. Johnson, G. L. Nemhauser, M. W. P. Savelsbergh, et P. H. Vance, "Branch-and-price : Column generation for solving huge integer programs", *X*, vol. 46, pp. 316–329, 1996.

C. Barnhart, A. M. Cohn, E. Johnson, D. Klabjan, G. Nemhauser, et P. Vance, "Airline crew scheduling", dans *Handbook of Transportation Science, International Series in Operations Research & Management Science.* Springer, US, 2003, vol. 56, pp. 517–560.

C. Barnhart et R. G. Shenoi, "An approximate model and solution approach for the long-haul crew pairing problem", *Transportation Science*, vol. 32, no. 3, pp. 221–231, 1998.

J. E. Beasley et B. Cao, "A tree search algorithm for the crew scheduling problem", *European Journal of Operational Research*, vol. 94, no. 3, pp. 517–526, 1996.

P. Belobaba, A. Odoni, et C. Barnhart, *The Global Airline Industry.* Wiley, 2012.

J. F. Benders, "Partitioning procedures for solving mixed-variables programming problems", *Numerische mathematik*, vol. 4, no. 1, pp. 238–252, 1962.

S. Bisaillon, J. F. Cordeau, G. Laporte, et F. Pasin, "A large neighbourhood search heuristic for the aircraft and passenger recovery problem", *4OR*, vol. 9, no. 2, pp. 139–157, 2011.

R. E. Bixby, J. W. Gregory, I. J. Lustig, R. E. Marsten, et D. F. Shanno, "Very large-scale linear programming : a case study in combining interior point and simplex methods", *Operations Research*, vol. 40, no. 5, pp. 885–897, 1992.

S. Bratu et C. Barnhart, "Flight operations recovery : New approaches considering passenger recovery", *Journal of Scheduling*, vol. 9, no. 3, pp. 279–298, 2006.

V. Cacchiani et J.-J. Salazar-González, "A heuristic approach for an integrated fleet-assignment, aircraft-routing and crew-pairing problem", *Electronic Notes in Discrete Mathematics, vol. 41, pp. 391–398, 2013.*

K. W. Campbell, R. B. Durfee, et G. S. Hines, “Fedex generates bid lines using simulated annealing”, *Interfaces*, vol. 27, no. 2, pp. 1–16, 1997.

J. Cao et A. Kanafani, “Real-time decision support for integration of airline flight cancellations and delays part i : mathematical formulation”, *Transportation Planning and Technology*, vol. 20, no. 3, pp. 183–199, 1997.

——, “Real-time decision support for integration of airline flight cancellations and delays part ii : algorithm and computational experiments”, *Transportation Planning and Technology*, vol. 20, no. 3, pp. 201–217, 1997.

C.-H. Chen, T.-K. Liu, J.-H. Chou, et C.-C. Wang, “Multiobjective airline scheduling : An integrated approach”, dans *SICE Annual Conference (SICE), 2012 Proceedings of.* IEEE, 2012, pp. 1266–1270.

I. T. Christou, A. Zakarian, J. M. Liu, et H. Carter, “A two-phase genetic algorithm for large-scale bidline-generation problems at delta air lines”, *Interfaces*, vol. 29, no. 5, pp. 51–65, 1999.

M. D. D. Clarke, “Development of heuristic procedures for flight rescheduling in the aftermath of irregular airline operations”, Cambridge, Mass. : Massachusetts Institute of Technology, Flight Transportation Laboratory, Rapp. tech., 1997.

——, “Branch-and-price : Column generation for solving huge integer programs”, *Operations Research*, vol. 4, no. 2, pp. 67–76, 1998.

M. D. D. Clarke et G. Laporte, “The airline schedule recovery problem”, Thèse de doctorat, University of Montreal, 1997.

J. Clausen, A. Larsen, J. Larsen, et N. J. Rezanova, “Disruption management in the airline industry ?concepts, models and methods”, *Computers & Operations Research*, vol. 37, no. 5, pp. 809–821, 2010.

A. M. Cohn et C. Barnhart, “Improving crew scheduling by incorporating key maintenance routing decisions”, *Operations Research*, vol. 51, no. 3, pp. 387–396, 2003.

J.-F. Cordeau, G. Stojković, F. Soumis, et J. Desrosiers, “Benders decomposition for simultaneous aircraft routing and crew scheduling”, *Transportation science*, vol. 35, no. 4, pp. 375–388, 2001.

P. R. Day et D. M. Ryan, “Flight attendant rostering for short-haul airline operations”, *Operations research*, vol. 45, no. 5, pp. 649–661, 1997.

G.-F. Deng et W.-T. Lin, “Ant colony optimization-based algorithm for airline crew scheduling problem”, *Expert Systems with Applications*, vol. 38, no. 5, pp. 5787–5793, 2011.

G. Desaulniers, J. Desrosiers, I. Ioachim, M. M. Solomon, F. Soumis, et D. Villeneuve, “A unified framework for deterministic time constrained vehicle routing and crew scheduling problems”, *Fleet Management and Logistics*, pp. 57–93, 1998.

G. Desaulniers, D. J., et M. Solomon, *Large-scale models in the airline industry.* Springer, US, 2005.

G. Desaulniers, J. Desrosiers, Y. Dumas, S. Marc, B. Rioux, M. M. Solomon, et F. Soumis, “Crew pairing at air france”, *European journal of operational research*, vol. 97, no. 2, pp. 245–259, 1997.

J. Desrosiers, Y. Dumas, M. Desrochers, F. Soumis, B. Sanso, et P. Turdeau, “A breakthrough in airline crew scheduling”, Springer, Rapp. tech., 1991.

J. Desrosiers et M. E. Lübbecke, *A Primer in Column Generation.* Springer, 2005.

J. Desrosiers, Y. Dumas, M. M. Solomon, et F. Soumis, “Time constrained routing and scheduling”, dans *Network Routing*, série Handbooks in Operations Research and Management Science, M. O. Ball, T. L. Magnanti, C. L. Monma, et G. L. Nemhauser, éds. Elsevier, 1995, vol. 8, pp. 35–139.

V. Dück, F. Wesselmann, et L. Suhl, “Implementing a branch and price and cut method for the airline crew pairing optimization problem”, *Public Transport*, vol. 3, no. 1, pp. 43–64, 2011.

N. Eggenberg, M. Bierlaire, et M. Salani, “A column generation algorithm for disrupted airline schedules”, École Polytechnique Federale de Lausanne, Rapp. tech., 2007.

W. El Moudani, C. A. N. Cosenza, M. De Coligny, et F. Mora-Camino, “A bi-criterion approach for the airlines crew rostering problem”, dans *Evolutionary Multi-Criterion Optimization.* Springer, 2001, pp. 486–500.

I. Elhallaoui, D. Villeneuve, F. Soumis, et G. Desaulniers, “Dynamic aggregation of set-partitioning constraints in column generation”, *Operations Research*, vol. 53, no. 4, pp. 632–645, 2005.

I. Elhallaoui, A. Metrane, F. Soumis, et G. Desaulniers, “Multi-phase dynamic constraint aggregation for set partitioning type problems”, *Mathematical programming*, vol. 123, no. 2, pp. 345–370, 2010.

T. Fahle, U. Junker, S. E. Karisch, N. Kohl, M. Sellmann, et B. Vaaben, “Constraint programming based column generation for crew assignment”, *Journal of Heuristics*, vol. 8, no. 1, pp. 59–81, 2002.

J. A. Filar, P. Manyem, et K. White, “How airlines and airports recover from schedule perturbations : a survey”, *Annals of Operations Research*, vol. 108, no. 1-4, pp. 315–333, 2001.

M. L. Fisher, “The lagrangian relaxation method for solving integer programming problems”, *Management science*, vol. 27, no. 1, pp. 1–18, 1981.

——, “An applications oriented guide to lagrangian relaxation”, *Interfaces*, vol. 15, no. 2, pp. 10–21, 1985.

M. Gamache, F. Soumis, D. Villeneuve, J. Desrosiers, et E. Gelinas, “The preferential bidding system at air canada”, *Transportation Science*, vol. 32, no. 3, pp. 246–255, 1998.

M. Gamache, F. Soumis, G. Marquis, et J. Desrosiers, “A column generation approach for large-scale aircrew rostering problems”, *Operations research*, vol. 47, no. 2, pp. 247–263, 1999.

C. Gao, E. Johnson, et B. Smith, “Integrated airline fleet and crew robust planning”, *Transportation Science*, vol. 43, no. 1, pp. 2–16, 2009.

A. M. Geoffrion, *Lagrangean relaxation for integer programming.* Springer, 1974.

I. Gershkoff, “Optimizing flight crew schedules”, *Interfaces*, vol. 19, no. 4, pp. 29–43, 1989.

B. Gopalakrishnan et E. L. Johnson, “Airline crew scheduling : state-of-the-art”, *Annals of Operations Research*, vol. 140, no. 1, pp. 305–337, 2005.

Y. Guo, “A decision support framework for the airline crew schedule disruption management with strategy mapping”, *Operations Research Proceedings 2004*, pp. 158–165, 2005.

Y. Guo, T. Mellouli, L. Suhl, et M. P. Thiel, “A partially integrated airline crew scheduling approach with time-dependent crew capacities and multiple home bases”, *European Journal of Operational Research*, vol. 171, no. 3, pp. 1169–1181, 2006.

C. A. Hjorring et J. Hansen, “Column generation with a rule modelling language for airline crew pairing”, dans *Proceedings of the 34th Annual Conference of the Operational Research Society of New Zealand*, 1999, pp. 133–142.

K. L. Hoffman et M. Padberg, “Solving airline crew scheduling problems by branch-and-cut”, *Management Science*, vol. 39, no. 6, pp. 657–682, 1993.

J. Hu et E. L. Johnson, “Computational results with a primal–dual subproblem simplex method”, *Operations Research Letters*, vol. 25, no. 4, pp. 149–157, 1999.

S. Irnich et G. Desaulniers, *Shortest Path Problems with Resource Constraints*, G. Desaulniers, J. Desrosiers, et M. Solomon, éds. Springer US, 2005.

N. Jafari et S. Zegordi, “Simultaneous recovery model for aircraft and passengers”, *Journal of the Franklin Institute*, vol. 348, no. 7, pp. 1638–1655, 2011.

A. I. Z. Jarrah, G. Yu, N. Krishnamurthy, et A. Rakshit, “A decision support framework for airline flight cancellations and delays”, *Transportation Science*, vol. 27, no. 3, pp. 266–280, 1993.

A. I. Jarrah et J. T. Diamond, “The problem of generating crew bidlines”, *Interfaces*, vol. 27, no. 4, pp. 49–64, 1997.

E. Johnson, L. Lettovsky, G. Nemhauser, R. Pandit, et S. Querido, “Final report to northwest airlines on the crew recovery problem”, The Logistic Institute, Georgia Institute of Technology, Atlanta, USA, Rapp. tech., 1994.

B. K., G. Desaulniers, et I. Elhallaoui, “Bidline scheduling with equity by heuristic dynamic constraint aggregation”, *Transportation Research Part B : Methodological*, vol. 44, no. 1, pp. 50–61, 2010.

A. Kasirzadeh, M. Saddoune, F. Soumis, et M. Towhidi, “Simultaneous optimization of personalized integrated scheduling for pilots and copilots”, École polytechnique de Montréal, Rapp. tech., 2014.

A. Kasirzadeh, M. Saddoune, et F. Soumis, “Airline crew scheduling : models, algorithms, and data sets”, *EURO Journal on Transportation and Logistics*, pp. 1–27, 2015.

D. Klabjan, E. L. Johnson, G. L. Nemhauser, E. Gelman, et S. Ramaswamy, “Solving large airline crew scheduling problems : Random pairing generation and strong branching”, *Computational Optimization and Applications*, vol. 20, no. 1, pp. 73–91, 2001.

——, “Airline crew scheduling with time windows and plane-count constraints”, *Transportation science*, vol. 36, no. 3, pp. 337–348, 2002.

N. Kohl, A. Larsen, J. Larsen, A. Ross, et S. Tiourine, “Airline disruption management–perspectives, experiences and outlook”, *Journal of Air Transport Management*, vol. 13, no. 3, pp. 149–162, 2007.

N. Kohl et S. E. Karisch, “Integrating operations research and constraint programming techniques in crew scheduling”, dans *Proceedings of the 40th Annual AGIFORS Symposium*, 2000, pp. 20–25.

——, “Airline crew rostering : Problem types, modeling, and optimization”, *Annals of Operations Research*, vol. 127, no. 1-4, pp. 223–257, 2004.

J. König et C. Strauss, “Supplements in airline cabin service”, dans *Information and Communication Technologies in Tourism 2000.* Springer, 2000, pp. 365–374.

——, “Rostering-integrated services and crew efficiency.” *J. of IT & Tourism*, vol. 3, no. 1, pp. 27–39, 2000.

S. Lavoie, M. Minoux, et E. Odier, “A new approach for crew pairing problems by column generation with an application to air transportation”, *European Journal of Operational Research*, vol. 35, no. 1, pp. 45–58, 1988.

L. Lettovsky, “Airline operations recovery : an optimization approach”, Thèse de doctorat, Georgia Institute of Technology, 1997.

L. Lettovsky, E. L. Johnson, et G. L. Nemhauser, “Airline crew recovery”, *Transportation Science*, vol. 34, no. 4, pp. 337–348, 2000.

T. K. Liu, C. R. Jeng, Y. T. Liu, et Y. H. Chang, “Disruption management of an inequality-based multi-fleet airline schedule by a multi-objective genetic algorithm”, *Transportation Planning and Technology*, vol. 31, no. 6, pp. 613–639, 2008.

M. Lohatepanont et C. Barnhart, “Airline schedule planning : Integrated models and algorithms for schedule design and fleet assignment”, *Transportation Science*, vol. 38, no. 1, pp. 19–32, 2004.

S. Luo et G. Yu, “On the airline schedule perturbation problem caused by the ground delay program”, *Transportation Science*, vol. 31, no. 4, pp. 298–311, 1997.

——, “Airline schedule perturbation problem : Landing and takeoff with nonsplitable resource for the ground delay program”, dans *International Series in Operations Research and Management Science*, 1998, vol. 9, pp. 404–432.

B. Maenhout et M. Vanhoucke, “A hybrid scatter search heuristic for personalized crew rostering in the airline industry”, *European Journal of Operational Research*, vol. 206, no. 1, pp. 155–167, 2010.

R. E. Marsten et F. Shepardson, “Exact solution of crew scheduling problems using the set partitioning model : recent successful applications”, *Networks*, vol. 11, no. 2, pp. 165–177, 1981.

R. K. Martin, *Large scale linear and integer optimization : a unified approach.* Springer Science and Business Media, 1999.

D. F. X. Mathaisel, “Decision support for airline system operations control and irregular operations”, *Computers & operations research*, vol. 23, no. 11, pp. 1083–1098, 1996.

C. P. Medard et N. Sawhney, “Airline crew scheduling from planning to operations”, *European Journal of Operational Research*, vol. 183, no. 3, pp. 1013–1027, 2007.

A. Mercier et F. Soumis, “An integrated aircraft routing, crew scheduling and flight retiming model”, *Computers & Operations Research*, vol. 34, no. 8, pp. 2251–2265, 2007.

A. Mercier, J.-F. Cordeau, et F. Soumis, “A computational study of benders decomposition for the integrated aircraft routing and crew scheduling problem”, *Computers & Operations Research*, vol. 32, no. 6, pp. 1451–1476, 2005.

M. Minoux, *Mathematical programming : theory and algorithms.* John Wiley & Sons, 1986.

R. Nissen et K. Haase, “Duty-period-based network model for crew rescheduling in european airlines”, *Journal of Scheduling*, vol. 9, no. 3, pp. 255–278, 2006.

N. Papadakos, “Integrated airline scheduling”, *Computers & Operations Research*, vol. 36, no. 1, pp. 176–195, 2009.

J. D. Petersen, G. Solveling, J. P. Clarke, E. L. Johnson, et S. Shebalov, “An optimization approach to airline integrated recovery”, *Transportation Science*, vol. 46, no. 4, pp. 482–500, 2012.

A. Rakshit, N. Krishnamurthy, et Y. Gang, “System operations advisor : a real-time decision support system for managing airline operations at united airlines”, *Interfaces*, vol. 26, no. 2, pp. 50–58, 1996.

J. Rosenberger, E. Johnson, et G. Nemhauser, “Rerouting aircraft for airline recovery”, *Transportation Science*, vol. 37, no. 4, pp. 408–421, 2003.

S. Ruther, “A multi-commodity flow formulation for the integrated aircraft routing, crew pairing, and tail assignment problem”, dans *Proceedings of the 45th annual conference of the ORSNZ*, 2010.

M. Saddoune, G. Desaulniers, I. Elhallaoui, et F. Soumis, “Integrated airline crew scheduling : A bi-dynamic constraint aggregation method using neighborhoods”, *European Journal of Operational Research*, vol. 212, no. 3, pp. 445–454, 2011.

——, “Integrated airline crew pairing and crew assignment by dynamic constraint aggregation”, *Transportation Science*, vol. 46, no. 1, pp. 39–55, 2012.

M. Saddoune, G. Desaulniers, et F. Soumis, “Aircrew pairings with possible repetitions of the same flight number”, *Computers & Operations Research*, vol. 40, no. 3, pp. 805 – 814, 2013.

R. Sandhu et D. Klabjan, “Integrated airline fleeting and crew-pairing decisions”, *Operations Research*, vol. 55, no. 3, pp. 439–456, 2007.

M. Sellmann, K. Zervoudakis, P. Stamatopoulos, et T. Fahle, “Crew assignment via constraint programming : integrating column generation and heuristic tree search”, *Annals of Operations Research*, vol. 115, no. 1-4, pp. 207–225, 2002.

H. D. Sherali, K.-H. Bae, et M. Haouari, “A benders decomposition approach for an integrated airline schedule design and fleet assignment problem with flight retiming, schedule balance, and demand recapture”, *Annals of Operations Research*, pp. 1–32, 2010.

M. Song, G. Wei, et G. Yu, “A decision support framework for crew management during airline irregular operations”, *Operations Research in the Airline Industry*, pp. 259–286, 1998.

N. Souai et J. Teghem, “Genetic algorithm based approach for the integrated airline crew-pairing and rostering problem”, *European Journal of Operational Research*, vol. 199, no. 3, pp. 674–683, 2009.

M. Stojković et F. Soumis, “An optimization model for the simultaneous operational flight and pilot scheduling problem”, *Management Science*, vol. 47, no. 9, pp. 1290–1305, 2001.

——, “The operational flight and multi-crew scheduling problem”, *Yugoslav Journal of Operations Research*, vol. 15, no. 1, 2005.

M. Stojković, F. Soumis, et J. Desrosiers, “The operational airline crew scheduling problem”, *Transportation Science*, vol. 32, no. 3, pp. 232–245, 1998.

S. Subramanian et H. D. Sherali, “An effective deflected subgradient optimization scheme for implementing column generation for large-scale airline crew scheduling problems”, *INFORMS Journal on Computing*, vol. 20, no. 4, pp. 565–578, 2008.

K. T. Talluri, “Swapping applications in a daily airline fleet assignment”, *Transportation Science*, vol. 30, no. 3, pp. 237–248, 1996.

D. Teodorović et S. Guberinić, “Optimal dispatching strategy on an airline network after a schedule perturbation”, *European Journal of Operational Research*, vol. 15, no. 2, pp. 178–182, 1984.

D. Teodorović et G. Stojković, “Model for operational daily airline scheduling”, *Transportation Planning and Technology*, vol. 14, no. 4, pp. 273–285, 1990.

B. Thengvall, J. Bard, et G. Yu, “Balancing user preferences for aircraft schedule recovery during irregular operations”, *IIE Transactions*, vol. 32, no. 3, pp. 181–193, 2000.

B. Thengvall, G. Yu, et J. Bard, “Multiple fleet aircraft schedule recovery following hub closures”, *Transportation Research Part A : Policy and Practice*, vol. 35, no. 4, pp. 289–308, 2001.

B. Thengvall, J. Bard, et G. Yu, “A bundle algorithm approach for the aircraft schedule recovery problem during hub closures”, *Transportation Science*, vol. 37, no. 4, pp. 392–407, 2003.

P. H. Vance, C. Barnhart, E. L. Johnson, et G. L. Nemhauser, “Airline crew scheduling : A new formulation and decomposition algorithm”, *Operations Research*, vol. 45, no. 2, pp. 188–200, 1997.

D. Villeneuve, “Logiciel de génération de colonnes”, Thèse de doctorat, 1999.

D. Wedelin, “An algorithm for large scale 0–1 integer programming with application to airline crew scheduling”, *Annals of operations research*, vol. 57, no. 1, pp. 283–301, 1995.

G. Wei, G. Yu, et M. Song, “Optimization model and algorithm for crew management during airline irregular operations”, *Journal of Combinatorial Optimization*, vol. 1, no. 3, pp. 305–321, 1997.

O. Weide, D. Ryan, et M. Ehrgott, “An iterative approach to robust and integrated aircraft routing and crew scheduling”, *Computers & Operations Research*, vol. 37, no. 5, pp. 833–844, 2010.

J. D. Weir et E. L. Johnson, “A three-phase approach to solving the bidline problem”, *Annals of Operations Research*, vol. 127, no. 1-4, pp. 283–308, 2004.

S. Yan et Y. Tu, “Multifleet routing and multistop flight scheduling for schedule perturbation”, *European Journal of Operational Research*, vol. 103, no. 1, pp. 155–169, 1997.

S. Yan et D. Yang, “A decision support framework for handling schedule perturbation”, *Transportation Research Part B : Methodological*, vol. 30, no. 6, pp. 405–419, 1996.

G. Yu, M. Argüello, G. Song, M. S. M., et A. White, “A new era for crew recovery at continental airlines”, *Interfaces*, vol. 33, no. 1, pp. 5–22, 2003.

F. Zeghal et M. Minoux, “Modeling and solving a crew assignment problem in air transportation”, *European Journal of Operational Research*, vol. 175, no. 1, pp. 187–209, 2006.

D. Zhang et H. Lau, “A rolling horizon based algorithm for solving integrated airline schedule recovery problem”, *Journal of Automation and Control Engineering*, vol. 2, no. 4, pp. 332–337, 2014.

Y. Zhang et M. Hansen, “Real-time intermodal substitution : Strategy for airline recovery from schedule perturbation and for mitigation of airport congestion”, *Transportation Research Record*, vol. 2052, no. 1, pp. 90–99, 2008.

X. Zhao et J. Zhu, “Grey programming for irregular flight scheduling”, *Grey Systems and Intelligent Services, 2007. GSIS 2007. IEEE International Conference on*, pp. 1607–1611, 2007.