The following publication Eltoukhy, A. E. E., Chan, F. T. S., & Chung, S. H. (2017). Airline schedule planning: A review and future directions. Industrial Management and Data Systems, 117(6), 1201–1243 is published by Emerald and is available at https://doi.org/10.1108/IMDS-09-2016-0358.

Airline schedule planning: A review and future directions

Abdelrahman E.E. Eltoukhy, Felix T.S. Chan*, and S.H. Chung

Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hum, Hong Kong

*Corresponding Author

elsayed.abdelrahman@connect.polyu.hk

f.chan@polyu.edu.hk

mfnick@polyu.edu.hk

Structured Abstract:

Purpose – The purpose of this research work is twofold. Firstly, to carry out comprehensive literature review for state-of-the-art regarding airline schedule planning. Secondly, to identify some new research directions that help academic researchers and practitioners.

Design/methodology/approach – The authors mainly focus on the research work appeared in the last three decades. The search process was conducted using four keywords: “Flight scheduling”, “Fleet assignment”, “Aircraft maintenance routing”, “Crew scheduling” in all database searches. Also, the combination of the keywords was used to find the integrated models. Any duplications due to database variety, and non-English language papers were discarded.

Findings – The authors studied116 research papers and categorized them into five categories. In addition, according to the model characteristics, sub-categories were further identified. Moreover, after discussing up-to-date research work, the authors suggested some future directions in order to contribute to the existing literature.

Research limitations/implications – The presented categories and sub-categories were based on the model characteristics rather than the model formulation and solution methodology. One advantage of this classification is that it might help scholars to deeply understand the main variation between the models. Identifying future research opportunities should help academic researchers and practitioners to develop new models and improve the performance of to the existing models.

Practical implications – This study proposed some considerations in order to enhance the efficiency of the schedule planning process practically. For example, using the dynamic stackelberg game strategy for market competition in flight scheduling, considering re-fleeting mechanism under heterogeneous fleet for fleet assignment, and considering the stochastic departure and arrival times for aircraft maintenance routing.

Originality/value – In the literature, all the review papers focused only on one category of our five categories. Then, this category was classified according to the model formulation and solution methodology. However, in this work, the authors attempted to propose a comprehensive review for all categories for the first time, and develop new classifications for each category. The proposed classifications are hence novel and significant.

Keywords:

Flight scheduling, Fleet assignment, Aircraft maintenance routing, Crew scheduling.

Article Classification:

Literature review

1. Introduction

The airline industry is characterized by the tight competitive market, high operational cost, variable passenger demand, heavy traffic, and strong regulations. In this situation, airline companies have to efficiently manage their resources that include flights, aircraft, and crews (Sherali et al., 2013a). In order to manage these resources, airline schedule planning problems are solved by the airline companies, while considering the vast number of regulations related to aircraft and crews that result in complex and non-tractable problems. Consequently, airline scheduling is decomposed into four stages: the *flight scheduling problem (FSP)*, the *fleet assignment problem (FAP)*, the *aircraft maintenance routing problem (AMRP)*, and finally the *crew scheduling problem (CSP)*. Traditionally, these problems are solved sequentially, where the solution in each stage is used as an input for the subsequent stage, as shown in Fig. 1.

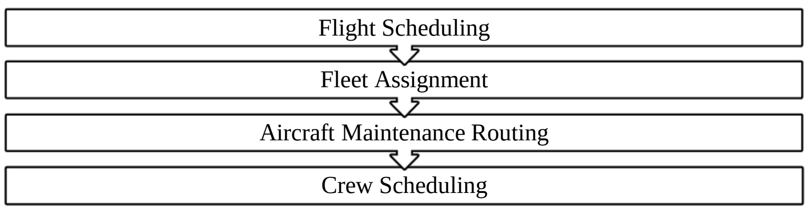

Fig. 1. The airline schedule planning processes

Fig. 1 describes the sequential operations that take place before the departure of an aircraft. At the beginning, the flight schedule is constructed considering marketing issues such as passenger demand and ticket price (Yan et al., 2007, Lee et al., 2007). Thereafter, each flight is covered by the specific aircraft type, and feasible maintenance routes are constructed for each fleet. These two steps are performed by fleet assignment (Rexing et al., 2000, Barnhart et al., 2002, Barnhart et al., 2009), and aircraft maintenance routing (Gopalan and Talluri, 1998, Sriram and Haghani, 2003, Sarac et al., 2006, Başdere and Bilge, 2014). In the last stage, cabin crew and cockpit are assigned to each flight in order to form an anonymous pairing, while satisfying the regulations and contractual issues (Vance et al., 1997, Ehrgott and Ryan, 2002, Zeghal and Minoux, 2006, Muter et al., 2013). The generated pairings are grouped in order to form personal rosters, considering vacations and crew requests. Although there are interrelations between each stage, they are usually solved sequentially due to their complexity. The sequential approach leads to sub-optimality solution, which means the solution is optimal in one stage and not in others. In order to avoid this problem, scholars now pay much attention to solving more integrated airline scheduling models so as to ameliorate the solution quality and the anticipated profit of the airline companies (Mercier et al., 2005, Haouari et al., 2009, Sherali et al., 2013b, Cacchiani and Salazar-González, 2016). The airline schedule planning process is one of the challenging processes faced by airline companies since the vast number of regulations and rules need to be considered for each resource in the process. For aircraft, the maintenance requirements and number of flying hours should be satisfied during the planning. For crew members, union rules, restrictions on the flying time, and contractual issues should be respected in the planning process.

In the literature, it is observed that there is no effort can be found to cover all the stages of airline schedule planning. Most of contributions focus on one stage only, as shown by (Etschmaier and Mathaisel, 1985), (Sherali et al., 2006), and (Gopalakrishnan and Johnson, 2005) who focused on flight scheduling, fleet assignment, and crew scheduling, respectively. In these studies, the focused stage was classified according to the model formulation and solution methodology, which make it hard to relate and understand the main operational features of each research work. As a result, there is general lack of comprehensive view that considers all the stages of airline schedule planning and discusses their features and operational considerations. Therefore, in this paper, we focus on the nature of the problem and its operational considerations, and classify each stage based on the problem characteristics rather than solution methodology and formulation methods. The main benefit of this classification over existing classification lies in its ability to give precise and in-depth sub-categories of each problem in airline schedule planning, thereby providing an insight into the progress of this field. So, the major contribution of this paper is to fill this gap and to facilitate the future work in this topic through two steps. Firstly, providing a map of what has been done in airline schedule planning by presenting an overview of the current state-of-the-art regarding airline schedule planning processes. Secondly, identifying some fertile opportunities for future research for researchers who are interested in the airline schedule planning field.

The remaining of this paper is organized as follows. In section 2, the research method is described. In section 3, the flight scheduling is presented. Section 4 presents the fleet assignment problem. In section 5, we describe the aircraft maintenance routing problem. The crew scheduling problem and its corresponding problems are discussed in section 6. In section 7, we survey the integrated airline schedule planning models. Finally, some concluding remarks and future research directions are presented in section 8.

2. Research method

2.1. Source of literature

The main objective of this research work is to provide an overview of the current state-of-the-art regarding airline scheduling planning processes, and identify some new research directions. In order to achieve this goal, we searched using three main sources: Science Direct – Online Journals by Elsevier Science; Emerald; Springer LINK Online Libraries. This survey is conducted based on articles in top journals, limited number of conference proceeding, handbooks, and theses.

As we mentioned that we need to provide a comprehensive survey for airline schedule planning, we mainly focused on the papers published in the last three decades. Also, any paper that cited significant contribution and out of this time frame is added to our survey, in order to enrich our review paper.

We conducted the search process using four keywords: “Flight scheduling”, “Fleet assignment”, “Aircraft maintenance routing”, and “Crew scheduling” in all database listed above. Also, we searched by using combination of keywords in order to find the integrated airline schedule planning models. During our search process, the papers were screened based on their quality, which were determined according to the impact factor of the journal, the total number of citations, and the journal ranking. In fact, our screening process was limited to the journals ranked as Q1, Q2, and Q3. In particular, we read each the screened papers and added any new article that didn’t appear in our first search. This allowed us to collect up-to-date research in our field. Any duplications due to database overlap, non-English language papers were discarded. Also, any paper that match with the keywords but its scope is not relevant to our categories was rejected.

The approach adopted in this paper is similar to that approach used by (Martínez-Costa et al., 2014) and (Chung et al., 2015) who provided a review for strategic capacity planning in manufacturing and disruption management in airline operations, respectively.

After making that search, 116 articles have been left, among which, there were 113 journal papers, one conference proceeding, one book chapter, and one thesis. In fact, the journal papers came from 27 different journals even though 75% of them came from top journals, as shown in table 1. Table 1 illustrates the journal used in the literature survey, the number of papers picked from each journal, the impact factor of each journal, and the number of citation. The content of this table indicate how good the papers are, as most of the papers came from top journals in the airline transportation planning.

2.2. The philosophy of the review work

The review work was conducted by following these three steps:

1. Identify the relevant literature concerning the airline schedule planning, and identify how identify how different classes of problems varied in terms of operational considerations.
2. Categorize the problem into five main group; flight scheduling, fleet assignment, aircraft maintenance routing, crew scheduling, and the integrated models.
3. Define sub-group for each main group according to the predetermined variants, discuss the main features of each sub-group, and summarize the main characteristics of each sub-groups’ models (objective function, solution methods, used data)

4. Suggest the new wave of research on the airline schedule planning.

2.3. Classification Schemes

There are many classification schemes in the literature to categorize the airline schedule planning. Using different solution methodology (e.g. exact methods, meta-heuristics), and formulation methods (e.g. set-partitioning, multi-commodity network flow, integer programming) are the most common used classification schemes in the previous work in order to provide airline schedule planning classification scheme. Since our focus on the nature of the problem and its operational considerations, our classification scheme is based on the problem characteristics rather than solution methodology and formulation methods. The main benefit of this classification scheme over existing scheme lies in its ability to give precise and in-depth sub-categories of each problem in airline schedule planning, thereby providing an insight into the progress of this field.

3. Flight Scheduling problem (FSP)

The first category in this paper is FSP, which is considered to be the first problem to be solved by airline companies before operation commences. FSP aims to generate a timetable that contains a list of flights with their corresponding origin, destination, departure time, and arrival time, while considering some marketing issues such as passenger demand and ticket price (Yan et al., 2007, Lee et al., 2007). Usually, the flight schedule is constructed at least 6 months in advance of the scheduled flight, with the objective of maximizing the expected profit. The FSP is usually solved in two steps; in the first step, the timetable is constructed, while evaluation of the generated timetable is carried out in the second step. The timetable evaluation is made by checking the feasibility of each flight leg, and ensuring cost minimization of each flight. In order to improve the constructed timetable, these two steps are repeated until no more improvements can be made. In order to build an efficient flight schedule timetable, the airline companies have to determine certain aspects such as the projected markets served, the type of flights (non-stop flights or connecting flights), and the frequency of the flights in each market.

After reading FSP papers, the flight scheduling models can be classified into two main sub-categories. The first sub-category includes the models that consider market share and passenger demand fluctuations, as described in section 3.1. The second sub-category groups the models that pay attention to the robustness of the generated timetable, as described in section 3.2. In section 3.3, Table 2 provides a summary of the models' characteristics in chronological order. In section 3.4, we provide a discussion for the reviewed FSP papers.

3.1. Passenger demand and market share in FSP

To build an efficient flight schedule, passenger demand fluctuations and the market share should be considered in the planning stage. (Yan and Young, 1996) were among the first authors who considered the expectation of demand variation, which enables the planning managers to modify the flight schedule that is built based on fixed passenger demand. The flight timetable adjustment can be done in different ways; deleting of multi-stop flight legs, or changing the departure time, or renting aircraft. The proposed model was tested by a case study on the international operations of a major Taiwan Airline, and the computational results showed that the model outperformed the trial and error method used by Taiwan Airlines. However, this paper has two drawbacks; the first one is the focus on one-stop and non-stop flights, and the second one is that the model neglects the market share consideration. (Yan and Tseng, 2002) improved the paper by (Yan and Young, 1996) by considering the market share in their model. The proposed model was solved with the objective of maximizing the system profit, but the passenger demand and projected market share were still fixed.

In order to relax the fixed market share assumption that was set by Yan and Tseng's model, (Yan et al., 2007) incorporated passenger demand choice to reflect a variable market share in their proposed model in order to improve the flight schedule in a competitive market. The authors developed a heuristic approach to solve the problem iteratively, and showed good performance during validation testing. In this model, we can say that the authors considered the variable market share, but the passenger demand was assumed to be fixed. The paper presented by (Jiang and Barnhart, 2009) considered the variability of passenger demand but neglected the market share. The authors developed a dynamic scheduling model that used a flight retiming mechanism in order to re-optimize the flight, and matched the stochastic passenger demand and aircraft seats. Based on data provided by a US airline, the authors reported that the annual saving increased from $18 million to $36 million.

In a trial that considered the variability of the market share and passenger demand simultaneously, (Yan et al., 2008) developed a two stage stochastic programming model that considered the two aspects, resulting in a highly complex model (NP-hard). In order to avoid high complexity, a single fleet with non-stop flight operation was considered in the constructed model. Based on data provided by Taiwan Airlines, comprised from 8 cities covered by 19 aircraft, the computational results showed good performance.

3.2. Robust flight scheduling models

Robustness is considered one of the interesting research directions in the airline schedule planning arena. The main goal of a robust flight schedule is to make the generated timetable less sensitive to disruptions. It is a pro-active way to absorb any changes that may happen in the scheduled timetable (Chung et al., 2015, Hing Kai and Alain Yee Loong, 2015). Actually, there are few research studies that pay attention to the robustness of FSP models. For example, (Lee et al., 2007) developed a model that improved solution robustness by increasing the adjustability of the flight departure time in the generated schedule timetable. The proposed model enabled the planning mangers to avoid disruptions by retiming the flight departure time without inserting or deleting any flights. The model was evaluated by using simulation model SIMAIR2.0, and it provided a schedule with lower costs and better on-time performance, but in longer computational time. To our best knowledge, the robustness can be achieved in two different ways; the first way is by constructing a reliable model with adjustable departure time that allows using the flight re-timing option as mentioned in (Lee et al., 2007). The second way is by constructing a flexible model that offers many swapping options for the aircraft. Both options are considered by (Burke et al., 2010) who improved the robustness of the original schedule by using the flight re-timing option and the swapping option. The model's flexibility and reliability were investigated by using real data from KLM Royal Dutch Airlines, and the results showed significant improvement in both objectives.

Another recent work on robust FSP was reported by (Sohoni et al., 2011). The authors considered the block time uncertainty as a measure of robustness. Stochastic integer programming was developed in order to optimally adjust the generated schedule to maximize the expected profit. Based on real data, the model was solved by an efficient algorithm based on cut generation techniques, and the computational results showed good performance. Recently, (Jiang and Barnhart, 2013) proposed a robust model, where the robustness is measured by the number potentially connected itinerary.

3.3. Characteristics of the models

This section presents other characteristics of the reviewed flight scheduling models. As the result of the survey carried out, Table 2 classifies the models according to the following factors: planning horizon, network representation, model formulation, objective function of the model, solution procedure, with the authors demonstrating the computational study with real data or using generated data. Other features are presented in the last six columns of Table 2.

3.4. Discussion

After reviewing the papers regarding market share and passenger demand, we can see that there is a sequence of effort that its complexity increased gradually. This sequence starts with (Yan and Young, 1996) and (Yan and Tseng, 2002) who studied the fixed market share and passenger demand. Implementing these models in reality is quite uncertain, since they fail to consider the variability of market share and passenger demand, which is one the main characteristics of aviation industry. Later, another two studies emerged by (Yan et al., 2007) and (Jiang and Barnhart, 2009) who investigated the variability of one aspect of market share and passenger demand. Their research works are promising they moved toward the real aspects of airline industry while considering the variability of market share or passenger demand. Finally, the peak of the efforts appeared in (Yan et al., 2008) who presented stochastic model. The strength of this study appears while considering stochastic market share and passenger demand, which means capturing the reality. On the other hand, during the implementation, they used test cases which are very small and do not reflect the reality. Therefore, their computational experiments are not enough to show the applicability in real airline industry.

In terms of robust FSP models, few research attempts are observed by (Lee et al., 2007), (Burke et al., 2010), and (Sohoni et al., 2011). These research trials are easy to be implemented since they produce a timetable that less sensitive to disruptions.

In overall, we notice that the number FSP research work is relatively low compared to other categories, and this area still needs another research effort to be exerted to fill some research gap, as explained in the conclusion section.

4. Fleet Assignment problem (FAP)

FAP is considered the second category in our study, which plays an important role to determine which aircraft types will be selected to cover the scheduled flight legs. Moreover, the FAP has to satisfy that each flight leg should be covered by exactly one aircraft type, and the total number of aircraft belongs to the same type that cover different flight legs doesn't exceed the fleet size. This problem is solved with two different objective functions, which maximize the profit or minimize the assignment cost. With respect to the cost, there are different types of costs included in the assignment costs, such as operating cost, carrying cost, and spill cost. Finding the balance between aircraft capacities and passenger demand is a great challenge that faces planning mangers because of great impact of fleet assignment on the airline's profit. Imagine, for example, the assignment of a large aircraft to cover a flight leg with a limited number of passengers, and aircraft with a small number of seats is assigned to cover a trip with large number of passengers. In the first case, there are spoiled seats, whereas in the second case there are spilled passengers. Both cases are not favorable for airlines, so that the FAP should be solved based on accurate passenger demand forecasts. Using such models resulted in a $30 million as an increase in the annual revenue of US Airways (Barnhart et al., 2002).
In the following sections, we categorize the fleet assignment models (FAM) that are presented in the literature into sub-categories according to the model characteristics. Basic FAM is presented in section 4.1. In order to enhance basic FAM, researchers consider the variable departure time, network effect, robustness, as shown in sections 4.2, 4.3, and 4.4, respectively. In section 4.5, we discuss the demand driven re-fleeting FAM, where the weekly FAM is addressed in section 4.6. In section 4.7, Table 2 presents other characteristics of FAM. In section 4.8, we provide a discussion for FAP research work.

4.1. Basic Fleet assignment models

In this section, we present the FAM that constitute the base of the work in this field. These models assume that the flight schedule is solved and the timetable is generated. Also, these models are solved under the assumption that the schedule is repeated every day of the week (Daily planning horizon), in order to avoid high computational flexibility.

(Abara, 1989) was one of the first authors presenting basic FAM based on a connection network structure (in which the nodes represent the flight leg, and the arcs represent the possible connections), in order to find feasible connections or turns between two flight legs. Actually, Abara's formulation has major disadvantages, which are; a large number of connections increases the model's complexity and the model fails to solve the problem for heterogeneous fleets. Implementing the model on American Airlines resulted in improvement in the profitability of the company. Abara's work was extended by (Rushmeier and Kontogiorgis, 1997). They proposed a model that was solved by using some preprocessing methods instead of finding feasible turns or connections. The authors also considered the resource availability that is expressed by linear penalties for any violation to the preplanned resource utilization. They reported profit improvement of about $15 million at US Airways.

Another basic FAM was presented by (Hane et al., 1995), which was different from the underlying network structure. The presented model was formulated based on the time-space network, in which the nodes represent the departure and arrival events, whereas the arcs represent the flight legs. They proposed some preprocessing stages in order to reduce the size of the structured network, such as node aggregation, island isolation, and the removing of unnecessary ground arcs. This model can find fast solutions for real problems comprising 2500 flight legs and 11 fleet types.

Although basic fleet FAM determines which aircraft types will be selected to cover the scheduled flight legs, it has some downsides. For example, it fails to consider the network effect and the recapture of the spilled passenger.

Also, basic FAM does not consider the variability of departure times that provides flexibility to the model and many other features that are discussed in the following sections.

4.2. FAM with variable departure time

Variable departure time provides flexibility to the FAM as shown by (Levin, 1971). He was the first author to consider variable departure times in a form of integer programming with binary constraints. The proposed model was solved with a branch-and-bound approach instead of dynamic programming in order to reach the optimal solution. This model doesn't allow for the considering of aircraft capacity and multiple fleet types. The paper by (Desaulniers et al., 1997b) was basically an extension of Levin's work. The authors considered heterogeneous fleet as well variable departure times in their proposed model. The authors presented two different formulations for the fleet problem, which are set-partitioning formulation, and multi-commodity network flow model formulation, and proposed different branching strategies for solving the problem. They reported profit and tractability improvement after implementing their approach. Similar to Levin's model, (Rexing et al., 2000) proposed a model at which the departure time of each flight leg is discretized within specified time windows in order to increase the flight connection opportunities. The proposed model was solved by using two approaches; the first one was a direct approach by using commercial software which was good for speed and small sized problem, while the second one was an iterative approach which was appropriate for large scale problems. Actually, the authors reported potential savings of about $67000 in the operating cost beside the spill cost at US Airlines.

4.3. FAM with network effect

The network effect means that the demand that is coming from multi-leg passengers is dependent on the availability of seats on the flight legs. To our best knowledge, the Ph.D. dissertation by (Farkas, 1995) was one of the first research works that attempts to address the network effect in his proposed model. Farkas's model fails to consider the recapture of a spilled passenger, which was further considered by (Barnhart et al., 2002) who proposed an itinerary based model. The authors used a network of 2044 legs and 76641 paths in order to validate their model. They reported $30 million as an increase in the annual revenue of US Airline.

The next two papers consider stochastic passenger demand which was neglected in the previous two papers. (Jacobs et al., 2008) proposed a decomposition strategy to incorporate the network effect in the origin-destination FAM. Also, this model considered the stochastic passenger demand (demand uncertainty) by using the demand driven dispatch technique. This model shows a 2.8% profit improvement over the leg FAM. The authors reported that this model was adopted by many U.S., European, and Asian Airlines due to its ability to reduce the cost. Another recent work that considered stochastic passenger demand was reported by (Dumas et al., 2009). The authors enhanced their model by using the information from the passenger flow model. The proposed model considered the network effect, the recapture between itineraries, and the stochastic demand. The authors reported profit improvement in Air Canada.

4.4. Robust fleet assignment models:

The airline industry is most likely faced by disruptions and unforeseen circumstances. Hence, robust models are imperative so as to provide a solution that better withstands during disruption. Actually, robust FAM hasn't received much attention. (Rosenberger et al., 2004) developed a robust model that used the concept of isolate hubs, which generates many short cycles that is less sensitive to flight cancelation. This method of formulation showed better performance over traditional FAM. Another robust FAM model was presented by (Smith and Johnson, 2006) who increased the model flexibility by incorporating the station purity concept, which means limiting the number of fleets or crew compatible families that can serve each station. The model addressed the crew and maintenance issues. Because of the negative computational impact of addressing the station purity, the authors used the station decomposition based on column generation to solve the model. The authors estimated an annual saving of about $100 million because of reduced maintenance and crew operational cost in a major U.S. domestic airline.

4.5. Demand driven re-fleeting FAM

Demand driven re-fleeting is an approach that is used by airlines in response to demand uncertainty, operational disruptions, maintenance, and crew changes. This approach changes the initial fleet assignment based on updated demand information. As much of the forecasted data is accurate, the improvement will be significant, because there are many stages that depend on the fleet assignment, such as routing and crew assignment. Hence, it is very important to estimate demand accurately.

In this section, we review the models that address the demand driven re-fleeting concept. (Berge and Hopperstad, 1993) were among the first researchers who presented the demand re-fleeting concept to capture the demand fluctuation during fleet assignment. In order to solve the re-fleeting problem in a reasonable computational time, the authors proposed two heuristics. The first heuristic was called the Sequential Minimum Cost Flow Method (SMCF) that can find the solution in 4 min, whereas the second heuristic was called the Delta Profit Method (DELPRO) and it reaches the solution in 3 min, but it can find the swap opportunity in a restricted way. Based on real data provided by a US domestic carrier, the computational results showed 1-5% improvement in the operating profits as a consequence of applying the demand driven re-fleeting approach. Berge and Hopperstad's work was extended by (Talluri, 1996) who improved the DELPRO heuristic in terms of swapping opportunities and computational time. On a data set provided by USAir, Talluri's algorithm could find ten swap opportunities in 3 to 4 seconds.

Another re-fleeting model was presented by (Jarrah et al., 2000). The authors developed an efficient FAM that gives planning managers the opportunity to generate different feasible scenarios and select the most appropriate one. This kind of formulation avoids the manual modification made in the basic FAM during the re-fleeting process. The authors reported that the model can reach high quality solutions in 5 min. On an attempt to reduce the representation of demand driven re-fleeting model, (Sherali et al., 2005) studied the polyhedral structure of the re-fleeting model in order to make dynamic reassignment, under the condition of availability of the improved demand forecasts. The model could solve moderate sized problems with 5% optimal tolerance. On a real network of 5,098 flight legs and 64,247 paths, operated by United Airlines, the solution was generated within 20 min.

4.6. Weekly fleet assignment models

All the previous FAM models, except (Dumas et al., 2009, Berge and Hopperstad, 1993) assumed that the flight schedule is repeated every day of the week. From a practical point of view, Airlines permit some variations on the flight schedule of each day of the week in order to cope with demand fluctuation of different flight legs (for example the demand at weekend is higher than other days). In light of these facts, weekly FAM are more practical and profitable, as shown in the paper by (Bélanger et al., 2006). The authors presented weekly FAM with aircraft homogeneity that eased the process of ground service by using the same equipment to re-supply the aircrafts. On test instances involving up to 4400 flight legs, the results showed a significant increase in the anticipated profit of Air Canada.

Another weekly FAM was reported by (Pilla et al., 2008) who developed an approximation method for the profit function by using the regression splines fit. In a following paper, (Pilla et al., 2012) developed multivariate adaptive regression splines cutting planes as a solution methodology to solve the model. This method showed some improvement over the L-shaped method in the computational time, due to fast convergence. This model can capture the demand stochasticity but fails to consider the network effect and recapture of spilled passengers.

4.7. Other characteristics of FAM

As the result of our review for FAM, Table 3 summarizes the characteristics of the discussed models based on the planning horizon, network representation, objective function, and solution procedures. Also, the model's computational study and other features are presented on the same table.

4.8. Discussion

We observe significant efforts exerted to cover FAP in the literature since 1971. These efforts started by developing basic FAM, as shown by (Abara, 1989), (Hane et al., 1995), and (Rushmeier and Kontogiorgis, 1997). Although these models show a good contribution to the body of knowledge, they have some practical limitations. First, they assume that the flight schedule is repeated every day, which is far from reality. Second, they assume that the departure time for the flight leg is fixed and the passenger demand is deterministic. These assumptions reduce the applicability of these models in real aspects. These drawbacks of the basic FAM motivate the researchers to continue their effort to improve the models' applicability, as shown by (Desaulniers et al., 1997b) and (Rexing et al., 2000). These models' applicability is improved by considering the flexible departure time, which allows the mangers to make changes for the fleet assignments. However, these models have a downside, which is neglecting some operational considerations such as maintenance, crew, gate availability, and aircraft noise issues.

The improvement over basic FAM continued by (Barnhart et al., 2002) who considered the network effect that improves the model profitability. Their model shows significant profit improvement, but they use daily schedule which is not preferable by airline industry. Recently, the researchers paid attention to relax the deterministic assumption made by basic FAM as appeared on the work by (Jacobs et al., 2008), (Dumas et al., 2009) and (Pilla et al., 2012). These models can be easily implemented since they consider the network effect beside the stochastic demand, which enable capturing the real passenger demand.

Despite the greet effort that was observed while covering FAP, we notice few research work discussed the FAP robustness as a separate problem, as shown by (Rosenberger et al., 2004) and (Smith and Johnson, 2006). Their models provide a promising robust plan that better withstand during the disruption, but fail to consider the variable departure time, which is very important for real implementation. On contrast to FAP roundness, re-fleeting models received much attention from scholars, and their models show good performance in reasonable computational time as appeared in (Talluri, 1996) and (Jarrah et al., 2000).

A close look to table 3, FAP with heterogeneous fleet received less attention from the researchers as in (Talluri, 1996), because it increases the model complexity. Also, the weekly FAP was discussed by few studies like (Bélanger et al., 2006). They proposed a weekly model which is practical and profitable for airline companies.

5. Aircraft maintenance routing problem (AMRP)

After assigning each aircraft type or fleet to the scheduled flight legs, the airline company has to assign each specific aircraft to the scheduled flight legs, which can be done by solving the AMRP. This problem is considered the third category of the review paper. In AMRP, it is assumed that the previous stages, which are FSP and FAP, are already solved. AMRP aims to determine maintenance feasible route or the sequence of flight legs, which should be flown by each aircraft (tail number). The maintenance issues play an important role in determining the route of each aircraft, because each aircraft has to undergo maintenance checks after a certain period. The maintenance checks, which are mandated by Federal Aviation Administration (FAA), vary according to their frequencies and duration (Clarke et al., 1997). There are four types of maintenance checks, which should be considered by the airline operators to avoid any violation that may results in penalty fees. The first type is a Type A check and should be performed every 65 flight-hours, involving inspection of major parts, such as an aircraft engine. The second Type is a Type B check and is performed every 300-600 flight-hours, such as visual inspection and lubrication issues are carried out in this check type. The remaining two checks are Type C and Type D, they are carried out once every one to four years, respectively. Usually, the airline operates their maintenance checks under different regulations, which are more stringent than checks imposed by FAA. For example, each aircraft has to go for the *transit check* maintenance every 35-40 flying hours, where the visual inspection and minimum equipment list check are carried out. Another kind of maintenance is called the *balance check*. AMRP needs to incorporate the Type A maintenance check, as it is the most frequent one compared to other maintenance checks.

In the following sections, we review the Aircraft maintenance routing (AMR) models by discussing the different concerns, such as maintenance location and lines of flying, as shown in sections 5.1and 5.2, respectively. Also, different formulations are presented, i.e. string based models are discussed in section 5.3, network based formulation is presented in section 5.4, and section 5.4 presents asymmetric traveling salesman formulations. In section 5.6, we present the remaining time consideration. Table 4 summarizes the features of the reviewed models, as shown in section 5.7. In section 5.8, we provide a discussion regarding the AMRP models.

5.1. Maintenance location of AMR

In this section, we discuss the models that focus on finding the maintenance stations for each aircraft in order to meet maintenance requirements (each aircraft has to undergo maintenance once every four days). (Feo and Bard, 1989) presented the first integrated model of routing decisions and the maintenance base location, with the objective of minimizing the maintenance cost. Their proposed model can find the optimal number and location of maintenance stations that are required for the scheduled flight legs. Their model was cast as a multi-commodity network flow problem with integer restriction on the variables, and the model was solved by a two phase heuristics approach that reached the solution in 11 minutes. (Sriram and Haghani, 2003) extended Feo and Bard's work through considering the Type B maintenance check. An effective heuristic was developed to solve the problem in a reasonable computational time when compared with CPLEX.

5.2. Lines of flying (LOF) of AMR:

The previous two models' focus was to find the maintenance stations rather than finding the route for each aircraft. In this section, we present another sub-category of papers that focus on determining the route of each aircraft by using the Lines of flying (LOF) concept. A LOF is a sequence of flight legs starting and ending at airports where the aircraft undergoes maintenance at night. In order to solve the problem by using this concept, all feasible LOFs should be generated and the model will select the optimal among them. (Kabbani and Patty, 1992) were among the first researchers to use the concept of LOF to solve 3 day AMR. The authors formulated the AMR as a set-partitioning problem, where the rows and columns represent flights and routing, respectively. (Gopalan and Talluri, 1998) expanded the use of LOF to solve the k-days AMR. They developed an innovative polynomial time algorithm in order to determine maintenance feasible routes for aircrafts. The proposed algorithm was used to solve the static and dynamic formulations of the problem, where the routes were assumed to be fixed or allowed to be changed, respectively. The 2-day formulation of the problem was shown to be NP-Hard when the routes were allowed to be changed. (Talluri, 1998) merged the 3-day maintenance routing algorithm and polynomial time algorithm developed by (Gopalan and Talluri, 1998) in order to develop an effective heuristic to solve the 4-day aircraft maintenance routing problem.

5.3. String based models of AMR

One of the most powerful ways to find the best route for each aircraft in the fleet is using the string based approach. A string can be defined as a sequence of connected flights that starts and ends at a maintenance station, satisfying the flow balance and maximum flying time for each aircraft. The first string based model was developed by (Barnhart et al., 1998) who proposed an integrated model of fleet assignment and aircraft routing. The presented model can be used to solve the AMR only, by setting the number of fleet to one. The authors formulated the AMR as a set partitioning problem with side constraint and solved the problem by adoption a branch-and-price approach.

Another string based model was presented by (Sarac et al., 2006) who proposed an operational model for AMR. They incorporated into the model some important aspects that were ignored by other models, such as resource availability constraints (human resources and maintenance stations). As in (Barnhart et al., 1998), the problem was modeled as a set-partitioning problem and was solved by using branch-and-price method.

The major disadvantage of the string based approach is the large number of generated strings, which require using the column generation approach at each node of the branch-and-bound tree space. This situation leads to long computational time which is not preferred by airline companies.

5.4. Network based models of AMR

More recently, the network based approach was developed to avoid the drawbacks of the sting based models. This approach has many advantages, such as it has compact representation, can solve real life problems in a reasonable time, and can be tractable by commercial software.

Network based formulation first emerged on a paper presented by (Liang et al., 2011). They developed a new rotation-tour time-space network, and incorporated new arcs for representation through value and penalties values. The new model was very compact as its size was polynomial compared to the string model; this feature makes the model easy to be solved by commercial software. However, their model has many limitations. For example, it assumes that the maintenance is performed only at night, which is far from reality. Also, their computational experiments are not large scale enough to show the scalability and applicability of the proposed model, since they only solved a network with 352 flights and 70 aircraft. In a follow on paper, (Liang and Chaovalitwongse, 2012) expanded their previous work, by considering a more realistic and practical problem, the weekly AMR. The model was tested based on a real network of 5700 flights and 550 aircraft, and the solution was reached within 5 minutes.

5.5. Asymmetric travelling salesman formulation of AMR

The AMR can be formulated as the asymmetric travelling salesman (ATS) problem due to similarities between the two problems, as shown on a paper by (Clarke et al., 1997). The authors developed a model that aimed to find feasible maintenance rotations that maximize the through value (obtained from assigning one aircraft to cover certain connected flight legs). The authors fail to consider all the operational maintenance requirements. Also, (Mak and Boland, 2000) formulated the AMR as ATS model and solved it by adopting the simulated annealing method besides Lagrangian relaxation. The proposed approaches could reach the feasible solutions within 15-20 minutes.

5.6. Remaining time consideration of AMR

Remaining time is one of the important aspects, which is neglected by most of the AMR models. It can be defined as the difference between maximum allowed flying time for each aircraft and the accumulated flying time since the last maintenance operation. (Başdere and Bilge, 2014) considered the remaining time in their developed model. The authors focused on the operational point of view that considered the stochasticity and the possibility of cancelling and delaying the flights. The problem was formulated as a multi-commodity network flow model and it was solved by the use of both branch-and-bound and compressed annealing. The authors reported that compressed annealing outperformed branch-and-bound for large scale problems, and it could find feasible solutions in minutes, which is important for the airline industry.

5.7. Other characteristics of AMR models

In this section, Table 4 summarizes the AMR models' characteristics such as planning horizon, network representation, model formulation, solution procedure, and computational study. Also, maintenance checks and main considerations are presented in the last six columns of Table 4.

5.8 Discussion

After reviewing AMRP related studies, we can see that from 1992 up to 2000, the researchers pay much attention on proposing AMRP with tactical focus, as appeared by (Kabbani and Patty, 1992), (Clarke et al., 1997), (Gopalan and Talluri, 1998), (Talluri, 1998), and (Mak and Boland, 2000). These studies success in determining unique rotations or sequence of flight legs to be repeated every day by each aircraft, but fail to consider some of the operational maintenance requirements, such as the restrictions on the flying time, and the restrictions on the take-offs. Implementing these rotations practically is quite difficult due to lack of considering the operational requirements of the airline industry. Thus, the researchers move to propose AMRP with operational focus as appeared in the period from 2003 up to 2014. These studies aim to generate maintenance feasible routes to be flown by individual aircraft in the fleet, as shown in the studies by (Sriram and Haghani, 2003), (Sarac et al., 2006), and (Başdere and Bilge, 2014). (Sriram and Haghani, 2003) proposed an operational model and effective solution method, but their solution method can handle only small size problem with only 58 flights and 13 aircraft. This performance restricts their model applicability in the reality, since in reality the number of flights might reach up to 3000 flights. Similarly, in (Sarac et al., 2006), they proposed a model based on the commonly used set-partitioning formulation. However, a drawback of this approach is that it generates an exponential number of routes which needs a sophisticated method to solve the model, and it fails to handle real and large size problems. Lastly, in (Başdere and Bilge, 2014), the authors proposed an operational AMRP that shows good performance to handle large scale problems. However, this study fails to consider one important operational requirements mandated by FAA, which is the maximum take-offs between two successive maintenance operations.

In overall, we notice that AMRP received much attention from the scholars as show in table 4. However, there are some research gaps that is discussed in the last section of this paper.

6. Crew scheduling problem (CSP)

The CSP is considered the fourth category in our paper, and the last stage of the airline schedule planning process, and assumes that all previous stages are solved in advance. CSP is one of the most studied problems compared to other airline planning problems for the following reasons: Firstly, the crew cost is the second highest cost after the fuel cost so optimizing the CSP can make a significant reduction on the total operational cost of airline companies. Secondly, there are many regulations and contractual issues that should be considered in this problem, which increases the model complexity. In order to avoid the high complexity in CSP, the problem is solved sequentially in two steps. The first step is called the *crew pairing problem (CPP),* which provides, at a minimal cost, a set of pairing that will cover exactly once all the flight legs in the schedule, while satisfying the regulations and contractual issues. The second step is called the *crew rostering problem (CRP)* that uses the solution of the first step as an input, and provides the legal schedule for each crew member. To do that, there are many regulations and contractual restrictions that should be respected (Barnhart et al., 2003). In the remainder of this section, we discuss the CPP and CRP and their related models in the literature, as shown in sections 6.1 and 6.2, respectively. Also, in section 6.3, we present models that integrate both problems partially or totally. Table 5 closes this section and presents the main features of the reviewed crew scheduling papers, as shown in section 6.4. In section 6.5, we provide a discussion for reviewed CSP papers.

6.1. Crew pairing problem (CPP)

This is considered the first step of crew scheduling that must be solved in order to assign, at minimal cost, pairings to flight legs so that each flight in schedule is covered once, while considering the regulations posed by the FAA and the company rules, which may be different between airline companies. Each pairing or crew trip is usually a set of duties, starting and ending at the same crew base or hub. Each pairing should be assigned to crew members working in different positions, so that each flight is covered by the required attendants (pilot, copilot, stewards, and others...). One restriction for assigning two consecutive flights to the same crew member is that the connection time between the two flights should be sufficient for the crew member to move from one flight to other, but this constraint is relaxed if both flights are flown by the same aircraft. Actually, the crew pairing problem has received much attention since most of cost benefit lies in this part of crew scheduling process. In the following sections, we categorize the CPP in to sub-categories based on the model characteristics.

6.1.1. Basic crew pairing models

Basic crew pairing models (CPM) are developed in order to assign the generated pairing to the scheduled flight legs, while neglecting the uncertainty issues that are discussed in the following sections. In this section, we review such models, which can be categorized into two main groups; the daily pairing problem and the weekly pairing problem. In the daily problems, it is assumed that the flight schedule is repeated every day of the week, while in the weekly problems, it is assumed that each day of the week has different flight schedule.

Starting with the weekly problems, (Desaulniers et al., 1997a) presented a model that outperformed the system used by Air France due to considering accurate cost function. The proposed model considered the non-linear cost function without any approximation, which was neglected in other models, such as (Lavoie et al., 1988), and (Yan and Chang, 2002). The paper by (Klabjan et al., 2001) incorporated the idea of regularity in their model; meaning the crew will repeat itineraries, which eased the implementation and management processes. The model was solved by partitioning the legs into small groups and finding pairings in each group that can be repeated every day in the week. On the focus of cockpit pairing, (Yan and Chang, 2002) proposed a model for feasible pairing of the pilot, copilot, and flight engineer. For checking the applicability for their model, a case study was carried out at Taiwan Airways, regarding international operations covered by 7 aircraft types serving 444 flights. The model provided solutions in less than 10 seconds. Another weekly version of CPM appeared on the work by (Deng and Lin, 2011) who formulated the problem as a traveling salesman problem (TSP), and solved it by using an Ant colony optimization (ACO). ACO showed good potential tool to solve other scheduling problems in airline planning.

Moving to the daily problems, (Hoffman and Padberg, 1993) proposed Branch and Cut as a solution methodology for large scale problems, which couldn’t be solved by traditional approaches. On a trial to improve the performance of the CPM, (Barnhart et al., 1995) proposed a model that improved crew utilization through using deadhead crews, especially for long haul operation, that have long inactivity time. The model showed a significant reduction on the annual crew cost, reaching $5 million. There were some research attempts aim to improve the speed of solution and the overall performance of the CPM. For example, (Vance et al., 1997) presented a new formulation that depends on decomposing the problem into two sub-problems. The authors applied Dynamic Column Generation in order to reduce the number of variables and increase the speed of solution convergence.

6.1.2. CPM implemented by Airlines

In the literature, there are some successful attempts that aimed to improve the existing airline systems. For example, (Anbil et al., 1991) developed a SPIRIT approach to solve large scale problems efficiently by the usage of local improvement heuristics. Using such a model in US Airline, it realized annual savings of about $20 million. Also, (Graves et al., 1993) developed a new system for United Airlines, which worked efficiently in solving medium and large sized problems. The company yielded $16 million as an annual saving by using this system. In addition, (Chu et al., 1997) developed a model that provided a good pairing by the adoption of branching heuristics. The success of this model motivated American Airlines to use it as a planning system, which yields savings of $2 million annually.

6.1.3. Stochastic CPM

In the previous two sections, all the reviewed models are deterministic models that neglect the uncertainty issue, which is the main focus of this section. One CPM that considers the uncertainty was presented by (Schaefer et al., 2005) who developed a model that was better than the deterministic models. That model yielded good practical performance during the frictional disruptions over the deterministic models (e.g. the disruptions with limited duration such as weather changes, and airport congestion). This work was further extended by (Yen and Birge, 2006) who proposed a two stage stochastic model that captured proactively the interaction between long range and short range decisions. The computational results showed that airline companies can have significant savings when considering the uncertainty during the planning stage.

6.1.4. Robust CPM

The airline industry is often disrupted by external changes such as bad weather, technical problems, and others. So, developing robust pairing models that provide better solutions is really satisfying the needs of airline companies. In the paper proposed by (Ehrgott and Ryan, 2002), a robust model was developed for solving a model with two conflicting objectives, maximizing the robustness and minimizing the crew cost. They developed a Bi-criteria optimization approach that provided a Pareto optimal solution. They represented the robustness by penalizing any connection that have limited time and may cause delay. The model was tested using real world data and the results showed improvement in the robustness with a small increase in the cost. Another mechanism for robustness was presented by (Shebalov and Klabjan, 2006) who proposed a model that can provide robust solutions through maximizing the number of move-crews (crews that can be swapped). The model was solved by delayed column generation and Lagrangian relaxation. The model was evaluated by simulation; the model showed better performance over the traditional models in terms of robustness, cost and number of flight cancellations. The model provided a schedule with many swapping opportunities.

Moreover, (Tekiner et al., 2009) proposed the idea of extra flights as a source of disruption that should be managed at the planning stage. Swapping and deadhead options were used to manage these flights without making any delay or cancellation to the schedule. The authors proposed two robust integer programming models that provided robust solutions, but the major disadvantage of this model was that it solved only small size problems. In order to solve large scale problems, (Muter et al., 2013) extended Tekiner et al.'s work to develop an efficient column generation approach that could tackle real problems. They developed two pruning rules to enhance the column generation approach that was used to solve the pricing sub-problems.

6.2. Crew rostering problem (CRP)

The CRP is solved after the CPP in order to assign the generated pairing to each crew individually, taking into account vacations, crew requests, and skills, while considering the regulations, company rules, and union agreements. In this step, the crew schedule is generated so as all flights are covered by the required crew attendants (stewards and stewardess), and cockpit members (pilot, co-pilot, and flight engineer). The rosters are usually generated one month before the day of operation. The CRP is solved not only to minimize the operational cost, but also to maximize the social quality for each crew member by considering their preferences. In order to construct the monthly crew schedule there are two main methods; the rostering system and the preferential bidding system. In the following section, we discuss each method and the related work in the literature.

6.2.1. The rostering approach of CRP:

The rostering approach is adopted by many European airlines such as Air France, Alitalia, Lufthansa, and Swiss Air. This system is also used by Air New Zealand. The rostering approach constructs monthly crew schedules by generating individual rosters, taking into account the pre-assignment activities and crew requests. This approach attempts to provide a crew schedule which has a fair and equal share among crew members. The rostering approach has received much attention compared to the other method.

Rostering approach appeared on some work that focused on cabin crew rostering. For example, (Ryan, 1992) proposed a model with the aim of providing equitable rosters. The efficiency of the proposed work was appreciated by Air New Zealand and was implemented in 1989. In addition, (Day and Ryan, 1997) proposed a model to avoid manual allocation of rosters in Air New Zealand during the assigning duties and days-off for each crew member. The model is decomposed into the two parts. Firstly, assigning off days, and secondly assigning the pairings and other activities. Both sub-models are solved by adoption of column generation, but for each sub-model the total number of columns is quite limited compared to the case in which each sub-model are optimized simultaneously. The model was tested using real data provided by Air New Zealand; the results indicated that this method leaded to good solution quality only for short haul operations. Moreover, (Gamache et al., 1999) extended Day and Ryan's work by proposing an accelerated Column Generation approach. The results showed significant reduction on the computational time by a factor of more than 1000 with little deterioration on the solution quality.

On the other hand, rostering approach was used in papers with the focus on proposing meta-heuristics, specific algorithms, and new formulations. Regarding meta-heuristics, (Lučic and Teodorovic, 1999) used simulated annealing as a solution method for multi-objective problems. This method was tested by data instances provided by small and medium airline companies. With respect to specific algorithms, (Dawid et al., 2001) developed a SWIFTROSTER algorithm to solve real world problems. This algorithm was successful in solving problem involving 1300 crew members and 6 fleet types in reasonable computational time. On the focus of proposing new formulation different from set partitioning formulation, (Cappanera and Gallo, 2004) formulated the rostering problem as a multi-commodity flow problem where the crew members represent the commodity. The model representation was tight, and the computational experiments showed good performance to handle a medium size test instance delivered from Italian Airline.

More recently, (Maenhout and Vanhoucke, 2010) proposed a model that was quite different from the others. They presented a model that considered crew preference besides the pre-assignment activities, crew information, and regulations in order to maximize the social quality of the crew schedule. They used a hybrid scatter search approach in order to solve the problem that aimed to assign rosters to each crew member and decided if extra or freelance personnel should be hired.

While many research studies focused on cabin crew assignment as mentioned above, other research focused on pilot assignment by using the rostering approach. (Fahle et al., 2002) presented a model that captured all complex regulations neglected by the other models. Each airline regulation was expressed in the model. The model considered a real life case during the computational experiments, comprising 400 crew members and 1000 activities. This proposed model showed significant reduction on the computation time.

6.2.2. The preferential bidding approach of CRP

This approach is usually implemented by US and Canadian Airlines. Crew schedule can be constructed by this approach not only by considering the pre-assignment activities like the rostering approach, but also the crew preference that is reflected by weighted bids. This approach hasn't received much attention from researchers, because most airline companies prefer to adopt the rostering system.

(Gamache et al., 1998) presented a model for assigning pilots by using the preferential bidding method with the aim of maximizing an individuals' preference and the social quality of the schedule. The idea was to assign duties, days-off, and vacations by considering some weighted bids that reflected each individual preference. The problem was solved for each crew member starting from the most senior and ending with the most junior. Each solution means selecting the schedule with the best score for each individual. Air Canada substituted their current system with the system generated by this research in 1995 because of its significant improvement over its old system. On a trial to improve Gamache et al.'s work, (Achour et al., 2007) presented an exact method to solve the same problem. They improved the model by delaying the assignment of the best score schedule to the most senior member until there was only one remaining for that member. This method yielded a best score for the seniors without any effect of finding the best score for the others. This model was tested in real life problems, and showed solution quality improvement over the existing methods.

6.3. Integrated Crew scheduling problem

The crew scheduling model is usually decomposed into two separate models and each one is solved independently, leading to sub-optimal solutions. Integration the two models is a step forward to avoid sub-optimal solutions and it improves the overall performance of the scheduling system. Recently, scholars have paid attention to solving integrated crew scheduling problems in two different ways, sequentially (partial integration) or simultaneously (full integration).

Solving integrated crew scheduling sequentially appeared in the work by (Guo et al., 2006), who solved the pairing and rostering problems in a successive way. The model firstly selected the set of crew pairing, then, the model provided individual crew schedule by using the generated pairing. The authors reported that through this partial integration, there was a significant reduction in the total crew cost.

The sequential model has two main drawbacks, which are a lack of good cost estimation and neglecting the crew availability when a pairing problem is solved. These drawbacks motivated the researchers to solve the crew scheduling problems simultaneously as noticed by some scholars. For example, (Zeghal and Minoux, 2006) proposed a model for technical crew members (pilots and officers). In addition, (Souai and Teghem, 2009) proposed another model, while satisfying all the regulations and rules.

6.4. Other characteristics of crew scheduling models

Table 5 presents other characteristics of the reviewed models that weren't discussed in the previous sections. Table 5 summarizes these characteristics, which are; the planning horizon, type of network representation, objective function, solution procedure, and computational study. Moreover, other features of the models are presented in the last five columns of Table 5.

6.5. Discussion

After discussing CSP paper, we observe that it is the most studied part in the airline schedule planning. CSP mainly contains two parts; crew pairing and crew rostering.

Starting with crew pairing, we noticed that it received much attention than crew rostering. The reason behind that most of cost reduction can be achieved by producing an efficient pairing that minimize the operational cost. At the beginning, the researchers focus on studying CPP with daily planning horizon, such as (Hoffman and Padberg, 1993), (Barnhart et al., 1995), and (Vance et al., 1997). These studies show significant improvement to the solution methodology, since they can handle large scale problems. However, that solution will not be completely feasible in practice, because it assumes that all flown flights are repeated every day of the week. In reality, building pairing based on this assumption in not applicable, because one or more flights do not fly on the weekend or particular day. Therefore, the researchers avoid this issue and develop pairing models based on weekly planning horizon. For example, (Desaulniers et al., 1997a), (Yan and Chang, 2002), and (Klabjan et al., 2001). These studies avoid the limitations of the previous models and produce pairing to each specific day of the week. The discussed daily and weekly models assume that all departure time for the flights are fixed and know, which is proven to be wrong practically. Thus, the stochastic and robust crew pairing start to appear to cover this point as shown by (Ehrgott and Ryan, 2002), (Schaefer et al., 2005), (Yen and Birge, 2006), (Shebalov and Klabjan, 2006), (Tekiner et al., 2009), and (Muter et al., 2013). From practical side of view, the solution provided by these robust and stochastic models can be easily implemented in the real aviation industry.

Moving to the crew rostering, there are two approaches; the rostering approach and preferential bidding approach. Regarding rostering approach, (Ryan, 1992) presented a model that initially generate a set of feasible rosters and then solve the rostering problem. The performance of such approach depends on the quality of the rosters that are generated at the beginning. In (Day and Ryan, 1997) the authors used the standard column generation that fails to handle large scale problems. The rostering approach also investigated by other papers like (Gamache et al., 1999), (Lučic and Teodorovic, 1999), (Dawid et al., 2001), and (Maenhout and Vanhoucke, 2010). Although the rostering approach presented by the previous studies are implemented by many European airlines, it has one drawback. It does not give the individuals the chance to show their preference regarding the rosters resulting in assigning some rosters that are not preferred for those individual. On the other hand, the preferential bidding approach, received less attention compared to rostering approach. It successes to avoid the drawback of rostering approach, as shown by (Gamache et al., 1998) and (Achour et al., 2007).

We can see from table 5 that the cabin member scheduling received less attention than cockpit scheduling. This is because the cost related to cabin crew are significantly lower than the cockpit crew and also because the problem related to cabin crew is much large problem.

7. Integrated airline schedule planning models

In the previous sections, each airline planning process is solved sequentially and independently of the other processes to avoid computational complexity. Actually, the main drawback of this way is that the optimal solution of one process isn't optimal for the subsequent processes (sub-optimal solution), which leads to infeasible inputs to the other processes. This main drawback is one of the main reasons that motivates researchers to focus on integrating more than one schedule planning process simultaneously, so as so to ameliorate the solution quality and the anticipated profit of the airline companies. Although no attempts have been done to propose full integration of the four different planning processes, there are many integrated models of two or more different planning process that have been proposed. In this section, we present the last category that includes such integrated models, the solution techniques used for each model, and the implications of each model on the anticipated profit. In the last sub-section, we provide discussion regarding the integrated models.

7.1. FSP integrated with FAP

On the focus of integration between FSP and FAP, (Yan et al., 1997) proposed a model that adopted the option of aircraft rental in order to avoid demand fluctuation and market changes. The proposed model was tested through a case study in a major Taiwan Airline carrier, which covered 15 cities by 335 flights operated by 12 aircraft. The authors reported potential profit saving by using this model. Also, (Ioachim et al., 1999) studied the weekly FAP and incorporated schedule synchronization constraints for long haul operations. Their proposed model showed improvement in terms of the solution time, so it is efficient in tackling large scale real problems.

The interaction issue between passenger demand and flight supply was studied by (Yan and Tseng, 2002) and (Lohatepanont and Barnhart, 2004). With respect to Yan and Tseng's work, the authors proposed a model that assigned the aircraft and passenger simultaneously with the objective of minimizing the total cost. They developed a solution methodology that helped the model to converge within a 3% error gap. On the other hand, (Lohatepanont and Barnhart, 2004) presented a model that considered many aspects that were neglected by Yan and Tseng's model. These aspects are, for example, considering different fare class instead of aggregating it into one fare class, demand recapture, and flight leg interdependencies.

On an attempt to present a tight representation for FSP and FAM, (Sherali et al., 2009) performed polyhedral analysis and bender decomposition for their proposed model. They considered itinerary based demand and different fare classes. The authors validated their proposed model by using the data from US Airline, and using such a model resulted in $28.3 million increase in annual profit.

7.2. FAP integrated with AMRP

This kind of integration takes into account the interdependency between the two problems which leads to better and near optimal solutions. For the joint aircraft fleeting and routing problem, (Haouari et al., 2009) proposed a network flow based heuristics to solve their proposed integrated model. On the set of real data acquired from Tunis Air, the model could find very near optimal solutions in less than 8 seconds.

Another FAP integrated with AMRP was reported by (Zeghal et al., 2011) who incorporated the idea of renting out some aircraft during low demand seasons while hiring some aircraft during high demand periods. The model considered the fleet heterogeneity and long term maintenance issues. The authors reported that the model realized a $33.8 million increase in annual profit when testing the model by using real life data from Tunis Air. Short term and long term maintenance integrated with FAP were considered by (Haouari et al., 2011) who presented an exact solution approach to solve the integrated model, which was solved by using branch-and-price approach and benders decomposition. The first approach showing better performance over the second in finding the optimal solution, while the second was better in finding fast and near optimal solutions. The model could find optimal solution to a problem instance comprised of 507 rotations, 1050 flight legs and 34 aircraft from different types. However, the test instances are not big scale enough to test the applicability of the proposed methods in real industry. Weekly FAP integrated with AMRP was studied by (Liang and Chaovalitwongse, 2012) who proposed an innovative rotation tour network for modeling the problem. Recently, (Dong et al., 2016) presented a heuristic approach to solve the integrated model that considered the price elasticity of each itinerary. The results showed an achievement of significant profit improvement in a reasonable computation time.

7.3. AMRP integrated with CPP

The integrated AMRP and CPP models aim to determine, at minimum cost, a set of flight legs that are covered exactly by one aircraft and one crew base, while satisfying the maintenance requirements and other side constraints. Based on the AMRP integrated with CPP, (Cordeau et al., 2001) proposed a model that considered the maintenance issues and minimum connection time. To handle this kind of formulation, bender decomposition and column generation were used as the solution method. On test instance comprising 500 legs, the proposed model showed better crew cost reduction (9.4%) over the sequential approach. (Mercier et al., 2005) improved Cordeau et al.'s model to provide some penalties for connections that may delay, which in turn led to improve the solution robustness. The authors used two different bender decomposition methods and the Pareto cut method was studied to improve the speed of solution convergence.

Providing robust AMRP integrated with CPP was presented by (Weide et al., 2010). The authors tried to avoid the short and restricted connects, and used them as a mechanism for robustness. To solve such model, the authors used an iterative approach that stopped the iterations when there was no more opportunity to improve the solution robustness. Based on real world data, the model provided solutions with low cost and high robustness. Another robust model was discussed by (Dunbar et al., 2014) who incorporated stochastic delay information to their integrated model. The authors improved the robustness by minimizing the propagated delay. They proposed two algorithms to reduce the delay propagation by re-timing the routing and crew scheduling. The practical viability of the model was tested, and the computational results showed about 14% as an average reduction on the delay propagation.

All the previous papers in this section can be considered as a full integration between AMRP and CPP, which means the objective function has decision variables related to each problem. The next two papers attempted to provide partial integration of AMRP and CPP. The first attempt was introduced by (Klabjan et al., 2002) who incorporated plane count constraints so as to provide a crew schedule which maintained the maintenance feasibility at the same time. The model provided significantly better solutions than traditional pairing models. Another attempt for partial integration emerged on a study by (Cohn and Barnhart, 2003). The authors incorporated the maintenance issues in order to improve the performance of the crew scheduling model and reduce the total cost. This model guaranteed the maintenance feasible crew pairing solution.

7.4. FAP integrated with CPP

In the previous sections, scholars tried to integrate two consecutive planning processes, but in this section we discuss research works that integrate two non-consecutive planning problems such as FAP and CPP. For example, (Sandhu and Klabjan, 2007) proposed a full integration of fleeting and crew pairing, while neglecting the maintenance issues. The plane count constraint was used in order to capture the routing issue. The proposed model was solved in two different ways. Firstly, by the use of Lagrangian relaxation coupled with column generation, while the benders decomposition was acquired in the second method. The results showed a reduction of about 3% in the overall cost, and the performance of Lagrangian relaxation approach outperformed the benders decomposition method. Another FAP integrated with CPP appeared in a work by (Gao et al., 2009) who incorporated the station purity to their model by limiting both fleet types and available crew base in any airport. The proposed model was validated, and the results showed potential crew cost reduction ($4-8 million) besides amelioration of the solution robustness.

7.5. Integration of three different planning problems

In this section, we discuss research that aims to integrate more than two different airline planning processes. The complexity of these models is much higher than the others, but it provides better quality and near optimal solutions if compared with the previous models. The main challenge related to these models is how to find an appropriate solution approach in order to tackle the complexity of such models and to find the solution in a reasonable computational time, which is essential for the airline industry.

In a trial that integrated FSP, AMRP, and CPP, (Mercier and Soumis, 2007) introduced a model that permits some flexibility in the departure time. The model was solved by the application of the benders decomposition method coupled with dynamic constrained generation. The computational results showed reduction of crew cost and reduced aircraft usage.

Integrating the first three planning processes, FSP, FAP, and AMRP, received attention from (Sherali et al., 2013b). They proposed a complex model that considered many issues such as re-timing, demand recapture, maintenance issues, the through flights, and multiple fare classes. The high complexity of the model was handled by the application of the benders decomposition approach, and the computational results showed a 3% increase in the annual profit when compared with the traditional models. Also, (Gürkan et al., 2016) proposed a model that considered the cruise speed for the first time in order to increase the fuel utilization and decrease the number of needed aircraft.

On the other hand, there are some scholars interested in integrating FAP, AMRP, and CPP. For example, (Salazar-González, 2014) proposed a model that was implemented by a funded project in Spain to operate daily flights. The authors presented a new compact formulation for the model that was quite similar to the 2 depot vehicle routing problem, and provided an automatic approach to solve the problem instead of the efforts exerted by the planning mangers. Another attempt appeared by(Shao et al., 2015) who proposed a model with itinerary demands considerations, and developed some novel accelerating strategies for the benders decomposition approach in order to solve the proposed model. Recently, (Cacchiani and Salazar-González, 2016) developed a novel model, where arc based variables represent the aircraft routes and path based variables represent crew pairings. The developed model was solved using two methods, called path-path and arc path methods. The results showed that the second method outperformed the first one in finding the optimal solutions, while solving a real test cases up to 172 flights.

7.6. Other features of the reviewed integrated models

In this section, Table 6 summarizes all the features of the reviewed integrated models, which are; the planning horizon, type of network representation, objective function, the solution procedures, and the computational study.

7.7. Discussion

In the last two decades, we notice that the researchers interested in the integration between different airline problems. It is observed that the integration between AMRP and other phases received much attention from the scholars, while AMRP was discussed from the tactical point of view (Cordeau et al., 2001, Haouari et al., 2009, Weide et al., 2010, Zeghal et al., 2011, Haouari et al., 2011, Liang and Chaovalitwongse, 2012, Dunbar et al., 2014, Dong et al., 2016). These studies success to avoid the sub-optimality problem, but they fail to generate routes that are applicable in reality due to the lack of the operational considerations.

Recently, it is noticed that cruise speed in one the mechanisms that are used to produce robust models (Gürkan et al., 2016). For this approach, the cruise speed can be adjusted in order to decrease the flying time and reduce the delay propagation. Although the efficacy of this approach theoretically, but practically, it increases the fuel cost as the fuel consumption is increased.

In the focus robust AMRP integrated with CPP, (Weide et al., 2010), and (Dunbar et al., 2014) presented a model where AMRP was formulated based on the expected value of the non-propagated delay. Since the non-propagated delay is characterized by high level of uncertainty, these expected values may not properly reflect the final realization of the non-propagated delay, when implemented in reality. This will, in turn, lead to easily delay propagation, disrupted routes, and unrobust solution.

8. Conclusion and future research directions:

This paper aims to present an up-to date review for airline schedule planning process. We categorize and summarize the rends and development of the relevant papers in order to support the future research directions.

Accordingly, we conduct our survey by using the following keywords "Flight scheduling", "Fleet assignment", "Aircraft maintenance routing", and "Crew scheduling". After screening and rejecting unelected research works, 116 research works were left that satisfied our scope in this paper.

First of all, we have categorized the airline schedule planning into four main categories, which as, flight scheduling, fleet assignment, aircraft maintenance routing, crew scheduling, and integrated models. Then, based on the problem characteristics and operational considerations, a total of two sub-categories in flight scheduling, six sub-categories in fleet assignment, six sub-categories in aircraft maintenance routing, seven sub-categories in crew scheduling, and five sub-categories in integrated models are further identified. From the analysis, we notice that the most studied category is crew scheduling, followed by fleet assignment, then aircraft maintenance routing, and finally the flight scheduling. Recently, in the period from 2000 up to now, the researchers have paid much attention to study the integrated models since it is more realistic and critical especially from aviation's perspective. Lastly, after discussing the research work done in airline schedule planning, several work avenues can be identified as future research directions as follows:

- For flight scheduling problem:
  - Re-timing the departure time has been demonstrated to be a promising approach for robust flight scheduling (Lee et al., 2007). Here, the only drawback is assuming that rotation and crew issues are fixed and unchanged, since using such approach, the model will produce robust flight schedule, but for crew and rotations, the solution will be unrobust. This point limits the applicability of that model in real aspect. Therefore, we suggest constructing a robust model that considers the variability of rotations and crew, and solve them simultaneously. So, the generating solution will be robust. Consequently, the reliability of the flight scheduling can be increased.
  - The market competition is considered in the flight scheduling by incorporating passenger choice behavior, which reflects the company's market share (Yan et al., 2007). The market scope of that study is quite limited, because in the market, each company keeps changing their strategy after the knowledge of the others' market share, until reach the stability point in which each company maximizes its profit. In order to analyze opponents' actions in the market, we suggest using the dynamic Stackelberg game strategy for broad consideration of the market state. This would result in higher profitability for airline companies.
  - Dynamic flight scheduling is one of approaches used to handle the stochastic passenger demand (Jiang and Barnhart, 2009). As discussed in that paper, the original timetable is adjusted to match the stochastic demand. Here, this adjustment might make some conflicts between flight scheduling and sub-sequent phases such as maintenance and crew plans that were built based on the original timetable. Therefore, we propose evaluating the impact of dynamic scheduling to the maintenance and crew plans, in order to avoid that conflict. Consequently, the generated timetable will be more reliable and stable.
- For fleet assignment problem:
  - Re-fleeting is an approach that is used by airlines in response to demand uncertainty in order to changes the initial fleet assignment based on updated demand information. Most of re-fleeting models are limited to homogenous fleet due to crew concerns (Berge and Hopperstad, 1993, Sherali et al., 2005). The only drawback is that the re-fleeting possibilities are limited because all the aircraft belong to the same family, resulting in inflexible and inefficient re-fleeting process. On the other hand, if, for instance, the re-fleeting is discussed while the fleet is heterogeneous. In this situation, the number of re-fleeting possibilities will be increased which in turns increase the process flexibility, but the crew consideration scope will be broaden. Accordingly, in the future research, discussing re-fleeting process under heterogeneous fleet is promising as it increases the efficiency of the re-fleeting process.
- For aircraft maintenance routing problem:
  - The operational AMRP aims to generate maintenance feasible route. A route is maintenance feasible if it satisfies operational maintenance requirements such as the maximum number of days between successive maintenance operations, restrictions on the total accumulated flying hour, the total number of take-offs, and the workforce capacity of the maintenance stations. To our knowledge, there are only two studies that tried to consider most of the requirement (Barnhart et

al., 1998, Haouari et al., 2012), but these studies fail to consider workforce capacity. In this situation, the model might schedule aircraft to receive maintenance in one station with insufficient capacity, resulting in prolonging the maintenance time, leading to a delay to cover the next flights. Therefore, proposing the model to consider all these requirements in one model will be appreciated by the airline companies, since the model will be more applicable.

- Currently, all AMRP models are discussed based on deterministic arrival and departure times, as shown by (Sriram and Haghani, 2003), (Sarac et al., 2006), and (Başdere and Bilge, 2014). Practically, this assumption is proven to be wrong, since airline industry is often disrupted by external changes, causing changes in the arrival and departure times. Accordingly, in future research, proposing an AMRP model with stochastic time consideration is a promising direction as the robustness of the generated routes will be enhanced. To our best knowledge, it will be the first stochastic AMRP.
- The maintenance operation for aircraft is frequent and inevitable due to the regulation mandated by FAA. If, for instance, the model considers the capacity of the maintenance station as a fixed parameter (Sriram and Haghani, 2003, Sarac et al., 2006), and for any reason there are shortage in that capacity. In this situation, the aircraft will fail to resume its duty after finishing the maintenance operation, resulting in higher operational cost to find another aircraft to substitute the original one. Thus, the impact of delay in the maintenance station becomes very significant. Therefore, the uncertainties of the maintenance capacity should also be investigated in the future.

For crew scheduling problem:

- The rostering problem aims to assign each crew members to the previously generated pairing in order to construct the rosters, while the number of crew members is fixed (Gamache et al., 1999), (Lučic and Teodorovic, 1999), (Dawid et al., 2001), and (Maenhout and Vanhoucke, 2010). Since the airline industry is most likely faced by disruptions and unforeseen circumstances, so it might happen that the number of crew members decrease due to absence or illness of some members. In this situation, the whole rosters will be affected and the airline should find another member to cover the pairing, resulting in higher operational cast and disruption to the original rosters. Thus the effect of uncertainties of the crew members during the rostering is obvious and critical. Therefore, considering this point is a fruitful research direction.
- The integrated crew scheduling models are usually solved by adoption of the rostering approach for crew assignment (Zeghal and Minoux, 2006, Souai and Teghem, 2009). Although the rostering approach presented are implemented by many European airlines, it has one drawback. It does not give the individuals the chance to show their preference regarding the rosters, resulting in assigning some rosters that are not preferred for those individual. For a better social quality schedule, we suggest developing an integrated scheduling model, while considering the preferential bidding system for building the rosters, which provides each crew member with opportunity to state their preference in regard to the assignment.

➢ For integrated airline schedule planning problems

- The integrated AMRP with other phases was discussed based on tactical point of view for AMRP (Cordeau et al., 2001, Haouari et al., 2009, Weide et al., 2010, Zeghal et al., 2011, Haouari et al., 2011, Liang and Chaovalitwongse, 2012, Dunbar et al., 2014, Dong et al., 2016). These studies success in avoiding the sub-optimality problem, but they fail in generating routes that are applicable in reality due to the lack of the operational considerations. Therefore, we suggest proposing integration while AMRP discussed from its operational point of view. It will result in generating maintenance feasible routes that can be easily implemented in real life aspect.
- Although all of the integrated schedule planning models have been studied, the challenge remains due to study the full integration between all four phases of airline schedule planning. In this connection, the proposed model will be more realistic and critical, but the complexity of the model will be increased. Therefore, the necessity for sophisticated solution methodology is important in this situation.

References

Abara, J. (1989). "Applying Integer Linear Programming to the Fleet Assignment Problem". *Interfaces,* Vol.19 No. 4**,** PP. 20-28.

Achour, H., Gamache, M., Soumis, F. and Desaulniers, G. (2007). "An Exact Solution Approach for the Preferential Bidding System Problem in the Airline Industry". *Transportation Science,* Vol.41 No. 3**,** PP. 354-365.

Anbil, R., Gelman, E., Patty, B. and Tanga, R. (1991). "Recent Advances in Crew-Pairing Optimization at American Airlines". *Interfaces,* Vol.21 No. 1**,** PP. 62-74.

Balakrishnan, A., Chien, T.W. and Wong, R.T. (1990). "Selecting aircraft routes for long-haul operations: A formulation and solution method". *Transportation Research Part B: Methodological,* Vol.24 No. 1**,** PP. 57-72.

Barnhart, C., Boland, N.L., Clarke, L.W., Johnson, E.L., Nemhauser, G.L. and Shenoi, R.G. (1998). "Flight String Models for Aircraft Fleeting and Routing". *Transportation Science,* Vol.32 No. 3**,** PP. 208-220.

Barnhart, C., Cohn, A., Johnson, E., Klabjan, D., Nemhauser, G. and Vance, P. 2003. Airline Crew Scheduling. *In:* HALL, R. (ed.) *Handbook of Transportation Science.* Springer US.

Barnhart, C., Farahat, A. and Lohatepanont, M. (2009). "Airline Fleet Assignment with Enhanced Revenue Modeling". *Operations Research,* Vol.57 No. 1**,** PP. 231-244.

Barnhart, C., Hatay, L. and Johnson, E.L. (1995). "Deadhead Selection for the Long-Haul Crew Pairing Problem". *Operations Research,* Vol.43 No. 3**,** PP. 491-499.

Barnhart, C., Kniker, T.S. and Lohatepanont, M. (2002). "Itinerary-Based Airline Fleet Assignment". *Transportation Science,* Vol.36 No. 2**,** PP. 199-217.

Başdere, M. and Bilge, Ü. (2014). "Operational aircraft maintenance routing problem with remaining time consideration". *European Journal of Operational Research,* Vol.235 No. 1**,** PP. 315-328.

Bélanger, N., Desaulniers, G., Soumis, F. and Desrosiers, J. (2006a). "Periodic airline fleet assignment with time windows, spacing constraints, and time dependent revenues". *European Journal of Operational Research,* Vol.175 No. 3**,** PP. 1754-1766.

Bélanger, N., Desaulniers, G., Soumis, F., Desrosiers, J. and Lavigne, J. (2006b). "Weekly airline fleet assignment with homogeneity". *Transportation Research Part B: Methodological,* Vol.40 No. 4**,** PP. 306-318.

Berge, M.E. and Hopperstad, C.A. (1993). "Demand Driven Dispatch: A Method for Dynamic Aircraft Capacity Assignment, Models and Algorithms". *Operations Research,* Vol.41 No. 1**,** PP. 153-168.

Burke, E.K., De Causmaecker, P., De Maere, G., Mulder, J., Paelinck, M. and Vanden Berghe, G. (2010). "A multi-objective approach for robust airline scheduling". *Computers & Operations Research,* Vol.37 No. 5**,** PP. 822-832.

Cacchiani, V. and Salazar-González, J.-J. (2016). "Optimal Solutions to a Real-World Integrated Airline Scheduling Problem". *Transportation Science.*

Cadarso, L. and Marín, Á. (2013). "Robust passenger oriented timetable and fleet assignment integration in airline planning". *Journal of Air Transport Management,* Vol.26 No. 0**,** PP. 44-49.

Cappanera, P. and Gallo, G. (2004). "A Multicommodity Flow Approach to the Crew Rostering Problem". *Operations Research,* Vol.52 No. 4**,** PP. 583-596.

Chu, H.D., Gelman, E. and Johnson, E.L. (1997). "Solving large scale crew scheduling problems". *European Journal of Operational Research,* Vol.97 No. 2**,** PP. 260-268.

Chung, S.H., Ying Kei, T. and Choi, T.M. (2015). "Managing disruption risk in express logistics via proactive planning". *Industrial Management & Data Systems,* Vol.115 No. 8**,** PP. 1481-1509.

Clarke, L., Johnson, E., Nemhauser, G. and Zhu, Z. (1997). "The aircraft rotation problem". *Annals of Operations Research,* Vol.69 No. 0**,** PP. 33-46.

Clarke, L.W., Hane, C.A., Johnson, E.L. and Nemhauser, G.L. (1996). "Maintenance and Crew Considerations in Fleet Assignment". *Transportation Science,* Vol.30 No. 3**,** PP. 249-260.

Cohn, A.M. and Barnhart, C. (2003). "Improving Crew Scheduling by Incorporating Key Maintenance Routing Decisions". *Operations Research,* Vol.51 No. 3**,** PP. 387-396.

Cordeau, J.-F., Stojković, G., Soumis, F. and Desrosiers, J. (2001). "Benders Decomposition for Simultaneous Aircraft Routing and Crew Scheduling". *Transportation Science,* Vol.35 No. 4**,** PP. 375-388.

Daskin, M.S. and Panayotopoulos, N.D. (1989). "A Lagrangian Relaxation Approach to Assigning Aircraft to Routes in Hub and Spoke Networks". *Transportation Science,* Vol.23 No. 2**,** PP. 91-99.

Dawid, H., König, J. and Strauss, C. (2001). "An enhanced rostering model for airline crews". *Computers & Operations Research,* Vol.28 No. 7**,** PP. 671-688.

Day, P.R. and Ryan, D.M. (1997). "Flight Attendant Rostering for Short-Haul Airline Operations". *Operations Research,* Vol.45 No. 5**,** PP. 649-661.

Deng, G.F. and Lin, W.T. (2011). "Ant colony optimization-based algorithm for airline crew scheduling problem". *Expert Systems with Applications,* Vol.38 No. 5**,** PP. 5787-5793.

Desaulniers, G., Desrosiers, J., Dumas, Y., Marc, S., Rioux, B., Solomon, M.M. and Soumis, F. (1997a). "Crew pairing at Air France". *European Journal of Operational Research,* Vol.97 No. 2**,** PP. 245-259.

Desaulniers, G., Desrosiers, J., Dumas, Y., Solomon, M.M. and Soumis, F. (1997b). "Daily Aircraft Routing and Scheduling". *Management Science,* Vol.43 No. 6**,** PP. 841-855.

Díaz-Ramírez, J., Huertas, J.I. and Trigos, F. (2014). "Aircraft maintenance, routing, and crew scheduling planning for airlines with a single fleet and a single maintenance and crew base". *Computers & Industrial Engineering,* Vol.75 No. 0**,** PP. 68-78.

Dong, Z., Chuhang, Y. and Lau, H.Y.K.H. (2016). "An integrated flight scheduling and fleet assignment method based on a discrete choice model". *Computers & Industrial Engineering,* Vol.98 No. 195-210.

Dumas, J., Aithnard, F. and Soumis, F. (2009). "Improving the objective function of the fleet assignment problem". *Transportation Research Part B: Methodological,* Vol.43 No. 4**,** PP. 466-475.

Dunbar, M., Froyland, G. and Wu, C.-L. (2014). "An integrated scenario-based approach for robust aircraft routing, crew pairing and re-timing". *Computers & Operations Research,* Vol.45 No. 0**,** PP. 68-86.

Ehrgott, M. and Ryan, D.M. (2002). "Constructing robust crew schedules with bicriteria optimization". *Journal of Multi-Criteria Decision Analysis,* Vol.11 No. 3**,** PP. 139-150.

Etschmaier, M.M. and Mathaisel, D.F.X. (1985). "Airline Scheduling: An Overview". *Transportation Science,* Vol.19 No. 2**,** PP. 127-138.

Fahle, T., Junker, U., Karisch, S., Kohl, N., Sellmann, M. and Vaaben, B. (2002). "Constraint Programming Based Column Generation for Crew Assignment". *Journal of Heuristics,* Vol.8 No. 1**,** PP. 59-81.

Farkas, A. 1995. *The influence of network effects and yield management on airline fleet assignment decisions.* Ph.D. Dissertation, Ph.D. Dissertation, Massachusetts Institute of Technology, Cambridge, MA.

Feo, T.A. and Bard, J.F. (1989). "Flight Scheduling and Maintenance Base Planning". *Management Science,* Vol.35 No. 12**,** PP. 1415-1432.

Gamache, M., Soumis, F., Marquis, G. and Desrosiers, J. (1999). "A Column Generation Approach for Large-Scale Aircrew Rostering Problems". *Operations Research,* Vol.47 No. 2**,** PP. 247-263.

Gamache, M., Soumis, F., Villeneuve, D., Desrosiers, J. and Gélinas, É. (1998). "The Preferential Bidding System at Air Canada". *Transportation Science,* Vol.32 No. 3**,** PP. 246-255.

Gao, C., Johnson, E. and Smith, B. (2009). "Integrated Airline Fleet and Crew Robust Planning". *Transportation Science,* Vol.43 No. 1**,** PP. 2-16.

Gopalakrishnan, B. and Johnson, E.L. (2005). "Airline Crew Scheduling: State-of-the-Art". *Annals of Operations Research,* Vol.140 No. 1**,** PP. 305-337.

Gopalan, R. and Talluri, K.T. (1998). "The Aircraft Maintenance Routing Problem". *Operations Research,* Vol.46 No. 2**,** PP. 260-271.

Graves, G.W., Mcbride, R.D., Gershkoff, I., Anderson, D. and Mahidhara, D. (1993). "Flight Crew Scheduling". *Management Science,* Vol.39 No. 6**,** PP. 736-745.

Guo, Y., Mellouli, T., Suhl, L. and Thiel, M.P. (2006). "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.

Gürkan, H., Gürel, S. and Aktürk, M.S. (2016). "An integrated approach for airline scheduling, aircraft fleeting and routing with cruise speed control". *Transportation Research Part C: Emerging Technologies,* Vol.68 No. 38-57.

Hane, C., Barnhart, C., Johnson, E., Marsten, R., Nemhauser, G. and Sigismondi, G. (1995). "The fleet assignment problem: Solving a large-scale integer program". *Mathematical Programming,* Vol.70 No. 1-3**,** PP. 211-232.

Haouari, M., Aissaoui, N. and Mansour, F.Z. (2009). "Network flow-based approaches for integrated aircraft fleeting and routing". *European Journal of Operational Research,* Vol.193 No. 2**,** PP. 591-599.

Haouari, M., Shao, S. and Sherali, H.D. (2012). "A Lifted Compact Formulation for the Daily Aircraft Maintenance Routing Problem". *Transportation Science,* Vol.47 No. 4**,** PP. 508-525.

Haouari, M., Sherali, H., Mansour, F. and Aissaoui, N. (2011). "Exact approaches for integrated aircraft fleeting and routing at TunisAir". *Computational Optimization & Applications,* Vol.49 No. 2**,** PP. 213-239.

Hing Kai, C. and Alain Yee Loong, C. (2015). "Invited review paper on managing disruption risk in express logistics via proactive planning". *Industrial Management & Data Systems,* Vol.115 No. 8**,** PP.

Hoffman, K.L. and Padberg, M. (1993). "Solving Airline Crew Scheduling Problems by Branch-and-Cut". *Management Science,* Vol.39 No. 6**,** PP. 657-682.

Ioachim, I., Desrosiers, J., Soumis, F. and Bélanger, N. (1999). "Fleet assignment and routing with schedule synchronization constraints". *European Journal of Operational Research,* Vol.119 No. 1**,** PP. 75-90.

Jacobs, T.L., Smith, B.C. and Johnson, E.L. (2008). "Incorporating Network Flow Effects into the Airline Fleet Assignment Process". *Transportation Science,* Vol.42 No. 4**,** PP. 514-529.

Jarrah, A.I., Goodstein, J. and Narasimhan, R. (2000). "An Efficient Airline Re-Fleeting Model for the Incremental Modification of Planned Fleet Assignments". *Transportation Science,* Vol.34 No. 4**,** PP. 349-363.

Jiang, H. and Barnhart, C. (2009). "Dynamic Airline Scheduling". *Transportation Science,* Vol.43 No. 3**,** PP. 336-354.

Jiang, H. and Barnhart, C. (2013). "Robust airline schedule design in a dynamic scheduling environment". *Computers & Operations Research,* Vol.40 No. 3**,** PP. 831-840.

Kabbani, N.M. and Patty, B.W. Aircraft routing at American airlines. In Proceedings of the 32nd annual symposium of AGIFORS, 1992 Budapest, Hungary.

Kepir, B., Koçyiğit, Ç., Koyuncu, I., Özer, M.B., Kara, B.Y. and Gürbüz, M.A. (2016). "Flight-Scheduling Optimization and Automation for AnadoluJet". *Interfaces,* Vol.46 No. 4**,** PP. 315-325.

Klabjan, D., Johnson, E.L., Nemhauser, G.L., Gelman, E. and Ramaswamy, S. (2001). "Airline Crew Scheduling with Regularity". *Transportation Science,* Vol.35 No. 4**,** PP. 359-374.

Klabjan, D., Johnson, E.L., Nemhauser, G.L., Gelman, E. and Ramaswamy, S. (2002). "Airline Crew Scheduling with Time Windows and Plane-Count Constraints". *Transportation Science,* Vol.36 No. 3**,** PP. 337-348.

Lavoie, S., Minoux, M. and Odier, E. (1988). "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.

Lee, L.H., Lee, C.U. and Tan, Y.P. (2007). "A multi-objective genetic algorithm for robust flight scheduling using simulation". *European Journal of Operational Research,* Vol.177 No. 3**,** PP. 1948-1968.

Levin, A. (1971). "Scheduling and Fleet Routing Models for Transportation Systems". *Transportation Science,* Vol.5 No. 3**,** PP. 232-255.

Li, Y. and Tan, N. (2013). "Study on Fleet Assignment Problem Model and Algorithm". *Mathematical Problems in Engineering,* Vol.2013 No. 5.

Liang, Z. and Chaovalitwongse, W.A. (2012). "A Network-Based Model for the Integrated Weekly Aircraft Maintenance Routing and Fleet Assignment Problem". *Transportation Science,* Vol.47 No. 4**,** PP. 493-507.

Liang, Z., Chaovalitwongse, W.A., Huang, H.C. and Johnson, E.L. (2011). "On a New Rotation Tour Network Model for Aircraft Maintenance Routing Problem". *Transportation Science,* Vol.45 No. 1**,** PP. 109-120.

Lohatepanont, M. and Barnhart, C. (2004). "Airline Schedule Planning: Integrated Models and Algorithms for Schedule Design and Fleet Assignment". *Transportation Science,* Vol.38 No. 1**,** PP. 19-32.

Lučic, P. and Teodorovic, D. (1999). "Simulated annealing for the multi-objective aircrew rostering problem". *Transportation Research Part A: Policy and Practice,* Vol.33 No. 1**,** PP. 19-45.

Maenhout, B. and Vanhoucke, M. (2010). "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.

Mak, V. and Boland, N. (2000). "Heuristic approaches to the asymmetric travelling salesman problem with replenishment arcs". *International Transactions in Operational Research,* Vol.7 No. 4–5**,** PP. 431-447.

Martínez-Costa, C., Mas-Machuca, M., Benedito, E. and Corominas, A. (2014). "A review of mathematical programming models for strategic capacity planning in manufacturing". *International Journal of Production Economics,* Vol.153 No. 66-85.

Mercier, A., Cordeau, J.-F. and Soumis, F. (2005). "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.

Mercier, A. and Soumis, F. (2007). "An integrated aircraft routing, crew scheduling and flight retiming model". *Computers & Operations Research,* Vol.34 No. 8**,** PP. 2251-2265.

Muter, İ., İlker Birbil, Ş., Bülbül, K., Şahin, G., Yenigün, H., Taş, D. and Tüzün, D. (2013). "Solving a robust airline crew pairing problem with column generation". *Computers & Operations Research,* Vol.40 No. 3**,** PP. 815-830.

Ozdemir, Y., Huseyin, B. & Kemal, G.N. (2012). "Optimization of Fleet Assignment: A Case Study in Turkey". *International Journal of Optimization and Control : Theories & Applications,* Vol.2 No. 1**,** PP. 59-71.

Pilla, V.L., Rosenberger, J.M., Chen, V., Engsuwan, N. and Siddappa, S. (2012). "A multivariate adaptive regression splines cutting plane approach for solving a two-stage stochastic programming fleet assignment model". *European Journal of Operational Research,* Vol.216 No. 1**,** PP. 162-171.

Pilla, V.L., Rosenberger, J.M., Chen, V.C.P. and Smith, B. (2008). "A statistical computer experiments approach to airline fleet assignment". *IIE Transactions,* Vol.40 No. 5**,** PP. 524-537.

Pita, J.P., Barnhart, C. and Antunes, A.P. (2012). "Integrated Flight Scheduling and Fleet Assignment Under Airport Congestion". *Transportation Science,* Vol.47 No. 4**,** PP. 477-492.

Rexing, B., Barnhart, C., Kniker, T., Jarrah, A. and Krishnamurthy, N. (2000). "Airline Fleet Assignment with Time Windows". *Transportation Science,* Vol.34 No. 1**,** PP. 1-20.

Rosenberger, J.M., Johnson, E.L. and Nemhauser, G.L. (2004). "A Robust Fleet-Assignment Model with Hub Isolation and Short Cycles". *Transportation Science,* Vol.38 No. 3**,** PP. 357-368.

Rushmeier, R.A. and Kontogiorgis, S.A. (1997). "Advances in the Optimization of Airline Fleet Assignment". *Transportation Science,* Vol.31 No. 2**,** PP. 159-169.

Ryan, D.M. (1992). "The Solution of Massive Generalized Set Partitioning Problems in Aircrew Rostering". *The Journal of the Operational Research Society,* Vol.43 No. 5**,** PP. 459-467.

Saddoune, M., Desaulniers, G., Elhallaoui, I. and Soumis, F. (2011). "Integrated airline crew scheduling: A bi-dynamic constraint aggregation method using neighborhoods". *European Journal of Operational Research,* Vol.212 No. 3**,** PP. 445-454.

Salazar-González, J.-J. (2014). "Approaches to solve the fleet-assignment, aircraft-routing, crew-pairing and crew-rostering problems of a regional carrier". *Omega,* Vol.43 No. 0**,** PP. 71-82.

Sandhu, R. and Klabjan, D. (2007). "Integrated Airline Fleeting and Crew-Pairing Decisions". *Operations Research,* Vol.55 No. 3**,** PP. 439-456.

Sarac, A., Batta, R. and Rump, C.M. (2006). "A branch-and-price approach for operational aircraft maintenance routing". *European Journal of Operational Research,* Vol.175 No. 3**,** PP. 1850-1869.

Schaefer, A.J., Johnson, E.L., Kleywegt, A.J. and Nemhauser, G.L. (2005). "Airline Crew Scheduling Under Uncertainty". *Transportation Science,* Vol.39 No. 3**,** PP. 340-348.

Shao, S., Sherali, H.D. and Haouari, M. (2015). "A Novel Model and Decomposition Approach for the Integrated Airline Fleet Assignment, Aircraft Routing, and Crew Pairing Problem". *Transportation Science,* No.

Shebalov, S. and Klabjan, D. (2006). "Robust Airline Crew Pairing: Move-up Crews". *Transportation Science,* Vol.40 No. 3**,** PP. 300-312.

Sherali, H.D., Bae, K.-H. and Haouari, M. (2009). "Integrated Airline Schedule Design and Fleet Assignment: Polyhedral Analysis and Benders' Decomposition Approach". *INFORMS Journal on Computing,* Vol.22 No. 4**,** PP. 500-513.

Sherali, H.D., Bae, K.-H. and Haouari, M. (2013a). "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,* Vol.210 No. 1**,** PP. 213-244.

Sherali, H.D., Bae, K.-H. and Haouari, M. (2013b). "An Integrated Approach for Airline Flight Selection and Timing, Fleet Assignment, and Aircraft Routing". *Transportation Science,* Vol.47 No. 4**,** PP. 455-476.

Sherali, H.D., Bish, E.K. and Zhu, X. (2005). "Polyhedral Analysis and Algorithms for a Demand-Driven Refleeting Model for Aircraft Assignment". *Transportation Science,* Vol.39 No. 3**,** PP. 349-366.

Sherali, H.D., Bish, E.K. and Zhu, X. (2006). "Airline fleet assignment concepts, models, and algorithms". *European Journal of Operational Research,* Vol.172 No. 1**,** PP. 1-30.

Smith, B.C. and Johnson, E.L. (2006). "Robust Airline Fleet Assignment: Imposing Station Purity Using Station Decomposition". *Transportation Science,* Vol.40 No. 4**,** PP. 497-516.

Sohoni, M., Lee, Y.-C. and Klabjan, D. (2011). "Robust Airline Scheduling Under Block-Time Uncertainty". *Transportation Science,* Vol.45 No. 4**,** PP. 451-464.

Souai, N. and Teghem, J. (2009). "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.

Soumis, F., Ferland, J.A. and Rousseau, J.-M. (1980). "A model for large-scale aircraft routing and scheduling problems". *Transportation Research Part B: Methodological,* Vol.14 No. 1–2**,** PP. 191-201.

Sriram, C. and Haghani, A. (2003). "An optimization model for aircraft maintenance scheduling and re-assignment". *Transportation Research Part A: Policy and Practice,* Vol.37 No. 1**,** PP. 29-48.

Subramanian, R., Scheff Jr, R.P., Quillinan, J.D., Wiper, D.S. and Marsten, R.E. (1994). "Coldstart: Fleet Assignment at Delta Air Lines". *Interfaces,* Vol.24 No. 1**,** PP. 104-120.

Talluri, K. (1996). "Swapping Applications in a Daily Airline Fleet Assignment". *Transportation science,* Vol.30 No. 3**,** PP. 237-248.

Talluri, K.T. (1998). "The Four-Day Aircraft Maintenance Routing Problem". *Transportation Science,* Vol.32 No. 1**,** PP. 43-53.

Tekiner, H., Birbil, Ş.İ. and Bülbül, K. (2009). "Robust crew pairing for managing extra flights". *Computers & Operations Research,* Vol.36 No. 6**,** PP. 2031-2048.

Vance, P.H., Barnhart, C., Johnson, E.L. and Nemhauser, G.L. (1997). "Airline Crew Scheduling: A New Formulation and Decomposition Algorithm". *Operations Research,* Vol.45 No. 2**,** PP. 188-200.

Wang, Y., Sun, H., Zhu, J. and Zhu, B. (2015). "Optimization Model and Algorithm Design for Airline Fleet Planning in a Multiairline Competitive Environment". *Mathematical Problems in Engineering,* Vol.2015 No. 13.

Weide, O., Ryan, D. and Ehrgott, M. (2010). "An iterative approach to robust and integrated aircraft routing and crew scheduling". *Computers & Operations Research,* Vol.37 No. 5**,** PP. 833-844.

Yan, S. and Chang, J.-C. (2002). "Airline cockpit crew scheduling". *European Journal of Operational Research,* Vol.136 No. 3**,** PP. 501-511.

Yan, S., Ho, S.-P. and Yang, T.-H. (1997). "An integrated model for fleet routing, flight scheduling and aircraft rental planning". *Journal of the Chinese Institute of Industrial Engineers,* Vol.14 No. 3**,** PP. 247-256.

Yan, S., Tang, C.H. and Fu, T.C. (2008). "An airline scheduling model and solution algorithms under stochastic demands". *European Journal of Operational Research,* Vol.190 No. 1**,** PP. 22-39.

Yan, S., Tang, C.H. and Lee, M.C. (2007). "A flight scheduling model for Taiwan airlines under market competitions". *Omega,* Vol.35 No. 1**,** PP. 61-74.

Yan, S. and Tseng, C.H. (2002). "A passenger demand model for airline flight scheduling and fleet routing". *Computers & Operations Research,* Vol.29 No. 11**,** PP. 1559-1581.

Yan, S. and Young, H.F. (1996). "A decision support framework for multi-fleet routing and multi-stop flight scheduling". *Transportation Research Part A: Policy and Practice,* Vol.30 No. 5**,** PP. 379-398.

Yen, J.W. and Birge, J.R. (2006). "A Stochastic Programming Approach to the Airline Crew Scheduling Problem". *Transportation Science,* Vol.40 No. 1**,** PP. 3-14.

Zeghal, F.M., Haouari, M., Sherali, H.D. and Aissaoui, N. (2011). "Flexible aircraft fleeting and routing at "Tunis Air"". *The Journal of the Operational Research Society,* Vol.62 No. 2**,** PP. 368-380.

Zeghal, F.M. and Minoux, M. (2006). "Modeling and solving a Crew Assignment Problem in air transportation". *European Journal of Operational Research,* Vol.175 No. 1**,** PP. 187-209.

Table 1: The features of the journals used in the literature survey.

Journal	Number of papers	Impact factor	Total citation	Journal Ranking
Transportation Science	34	3.295	3945	Q1
European Journal of Operational Research	18	2.679	31744	Q1
Operations Research	10	1.777	10200	Q2
Computers & Operations Research	10	1.988	7545	Q1
Management Science	4	2.741	22776	Q1
Transportation Research Part B	4	3.769	7358	Q1
Transportation Research Part A	3	1.994	5024	Q2
Computers & Industrial Engineering	2	2.086	6357	Q2
Transportation Research Part C	1	3.075	4153	Q1

Note: the data collected in this table delivered from ISI web of knowledge.

Table 2: Characteristics of flight scheduling model.

Author/s (year)	**Planning horizon**	**Network**	**Model formulation**	**Objective function**	**Solution procedure**	**Computational study**		**Other Features of the model**					
								Stochastic	**Robustness**	**Passenger demand**		**Market share**	
						Data	**Airline**			**Fixed**	**variable**	**Fixed**	**variable**
Yan and Young (1996)	W	TSN	MCNF	Min scheduling and fleeting costs.	Lagrangian relaxation and Lagrangian heuristic	RL	Taiwan			√			
Yan and Tseng (2002)	NA	TSN	MCNF	Min passenger and fleeting costs.	Developed algorithm	RL	Taiwan			√		√	
Yan et al. (2007)	D	TSN	NLMIP	Min passenger and fleeting costs.	Developed heuristic	RL	Taiwan	√		√			√
Lee et al. (2007)	W	-	MILP	Min percentage of late arrivals and flight time credit.	Genetic algorithm	G	-		√	√			
Yan et al. (2008)	D	TSN	NLIP	Min fleet flows and expected costs.	Arc-based heuristic algorithm and Route-based	RL	Taiwan	√			√		√

					heuristic algorithms								
Jiang and Barnhart (2009)	D&W	TSN	MILP	Max revenue minus operating cost.	ILOG CPLEX 9.0	RL	U.S.	√			√		
Burke et al. (2010)	W	TSN	MCNF	Max Schedule flexibility and reliability.	Multi-meme memetic algorithm.	RL	KLM Royal Dutch	√	√	√			
Sohoni et al. (2011)	NA	-	IP	Max The expected profit.	New cut generation algorithm	RL	U.S. carrier	√	√	√			
Jiang and Barnhart (2013)	D	TSN	MILP	Max the total revenue.	A decomposition-based approach.	RL	U.S.		√				
Kepir et al. (2016)	D	TSN	MILP	Min the number of idle planes.	Heuristic Algorithm	RL	Turkish			√			

Planning horizon: daily (D) or weekly (W). Network: time-space network (TSN). Model formulation: NLMIP: non-linear mixed integer programming, NLIP: non-linear integer programming, MILP: mixed integer linear programming, MCNF: mutli-commodity network flow, IP: integer programming. Used Data: real life (RL) or generated (G).

Table 3: Characteristics of fleet assignment models.

Author/s (year)	Planning horizon	Network	Model formulation	Objective function	Solution procedure	Computational study		Other features						
						Data	Airline	VDT	NE	SR	RM	DR	SD	HF
Levin (1971)	D	TSN	ILP	Min the fleet size	Branch-and-Bound methods	NA	-	√						
Soumis et al. (1980)	D	TSN	MILP	Min the assignment and spill cost	Frank-Wolfe algorithm	NA	-							
Daskin and Panayotopoulos (1989)	D	TSN	ILP	Max the profit	Lagrangian relaxation approach	G	-							
Abara (1989)	D	CN	MCNF	Max revenue minus operating cost	NA	NA	-							
Balakrishnan et al. (1990)	D	TSN	MCNF	Max the profit	Lagrangian relaxation-based solution procedure	G	-							
Berge and Hopperstad (1993)	W	TSN	MCNF	Max the profit	1st: Sequential Minimum Cost Flow Method (SMCF)	RL	U.S. domestic carrier					√	√	

					2nd: Delta Profit Method (DELPRO)									
Subramanian et al. (1994)	D	TSN	MILP	Min the operating and passenger cost	OB1 interior point code and OSL mixed integer programming code	RL	Delta Air Lines							
Hane et al. (1995)	D	TSN	MCNF	Min the assignment cost	Interior-point algorithm and branching	RL	-							
Talluri (1996)	D	CN	MCNF	Min the swapping cost	Developed algorithm	RL	USAir					√		√
Rushmeier and Kontogiorgis (1997)	D	CN	MCNF	Max the profit	Software based on Linear programming relaxation, CPLEX, and rounding heuristic	RL	USAir							
Desaulniers et al. (1997b)	D	TSN	SP & MCNF	Max anticipated profit	1st: Linear relaxation and application of column generation. 2nd: Linear relaxation and application of Dantzig-Wolfe decomposition.	RL	1st:North-American carrier. 2nd:European carrier	√						√
Rexing et al. (2000)	D	TSN	MILP	Min the assignment cost	1st: Direct solution approach 2nd: Iterative solution approach	RL	U.S.	√						
Jarrah et al. (2000)	D	TSN	MCNF	Max the revenue minus operating cost	Developed algorithm	RL	United Airlines					√		
Barnhart et al. (2002)	D	TSN	MILP	Min spill, carrying, and operating cost	Developed algorithm	RL	U.S.		√	√				
Rosenberger et al. (2004)	NA	TSN	MCNF	Min the assignment cost	Developed algorithm	G&RL	United Airlines				√			
Sherali et al. (2005)	NA	TSN	MILP	Max revenue	Polyhedral analysis-based approach	G&RL	United Airlines					√		
Bélanger et al. (2006b)	W	TSN	MCNF	Max profit minus fixed cost and penalties	1st: CPLEX 6.5 2nd: Developed Two-phase heuristic approach	RL	Air Canada						√	
Bélanger et al. (2006a)	D	TSN	MCNF	Max profit minus fixed cost and penalties	Branch-and-price approach	RL	North-American carrier.							
Smith and Johnson (2006)	D&W	TSN	MCNF	Max the profit	1st: Column generation and primal-dual method. 2nd: Fix-and-price heuristic	RL	U.S.				√			

Jacobs et al. (2008)	D	TSN	MCNF	Max overall profit	Developed algorithm	RL	American Eagle		√				√	
Barnhart et al. (2009)	D	TSN	MILP	Max the expected profit contribution	Developed algorithm	RL	U.S.							
Dumas et al. (2009)	W	TSN	MCNF	Min the assignment cost and revenue loss	Developed algorithm	RL	Air Canada		√	√			√	
Ozdemir et al. (2012)	D	TSN	ILP	Min the assignment cost	Lindo 6.1	RL	Turkish			√				
Pilla et al. (2012)	W	TSN	MCNF	Max the expected profit.	1st: L-shaped method 2nd:Multivariate adaptive regression splines cutting plane method	RL	-						√	
Li and Tan (2013)	D	TSN	ILP	Max the revenue.	Genetic algorithm	G	-							
Wang et al. (2015)	D	TSN	NMIP	Max the profit.	Developed algorithm	RL	-							

Planning horizon: daily (D) or weekly (W). Network: connection network (CN) or time-space network (TSN). Model formulation: multi-commodity network (MCNF), set-partitioning (SP), integer linear programming (ILP), non-linear mixed integer programming (NMIP) or mixed integer linear programming (MILP). Used Data: real life (RL) or generated (G). Other features: variable departure time (VDT), network effect (NE), spill recapture (SR), robust model (RM), dynamic re-fleeting (DR), stochastic demand (SD), Heterogeneous fleet (HF).

Table 4: Characteristics of aircraft maintenance routing models.

Author/s (year)	**Planning horizon**	**Network**	**Model formulation**	**Objective function**	**Solution procedure**	**Computational study**		**Other Features**					
								Maintenance checks				**Main consideration**	
						Data	**Airline**	A	B	T	BL	OP	TL
Feo and Bard (1989)	4D	CN	MCNF	Min maintenance cost	Chvatal's set covering heuristic	RL	American	√ (Night)				√	
Kabbani and Patty (1992)	3D	-	SP	Min total cost	Developed heuristic	RL	American	√					√
Clarke et al. (1997)	NA	TSN	ATS	Max through value	Lagrangian relaxation and subgradient optimization	RL	U.S.						√
Talluri (1998)	4D	-	EL	Finding feasible routes	3 day algorithm and Polynomial time algorithm	NA	-			√ (Night)			√

Gopalan and Talluri (1998)	3D	CN	EL	Finding feasible routes	Polynomial time algorithm	RL	-			√ (Night)	√ (Night)		√
Barnhart et al. (1998)	W	CN	SP	Min maintenance cost of selected strings	Branch and price, and cut algorithm	G	-						√
Mak and Boland (2000)	NA	CN	ATS	Max utilization of Remaining flying time	Simulated annealing, Lagrangian heuristic, and subgradient optimization	G	-						√
Sriram and Haghani (2003)	W	CN	MCNF	Min maintenance and re-assignment cost	Hybrid of random search and depth first search	G	-	√ (Night)	√ (Night)			√	
Sarac et al. (2006)	D	CN	SP	Min number of unused legal flying hours	Branch and price approach	RL	U.S.	√	√			√	
Liang et al. (2011)	D	TSN	NF	Min the connection cost and maintenance cost	CPLEX callable library version 10.0.	RL	U.S. carrier			√ (Night)			√
Liang and Chaovalitwongse (2012)	W	TSN	NF	Min Total penalty cost	Diving heuristic	RL	U.S.			√ (Night)			√
Haouari et al. (2012)	D	CN	NAFF	Finding feasible routes	CPLEX 12.1	RL	U.S.	√				√	
Başdere and Bilge (2014)	W	CN	MCNF	Max utilization of Remaining flying time	1st: Branch-and- bound 2nd: Compressed annealing heuristic.	RL	-					√	

Planning horizon: daily (D), 3days or 4days (3D, 4D) or weekly (W). Problem formulation: network flow (NF), multi-commodity network flow (MCNF), Euler tour (ET), asymmetric traveling salesman (ATS), set-partitioning (SP) or node arc flow formulation (NAFF). Maintenance checks: type A (A), type B (B), transit (T), or Balance (BL). Main consideration: tactical (TL) or operational (OL). Used Data: real life (RL) or generated (G).

Table 5: Characteristics of crew scheduling models.

Author/s (year)	Problem Tackled		Planning Horizon	Network	Model formulation	Objective function	Solution procedure	Computational study		Other features				
	CPP	CRP						Data	Airline	BCPM	RM	SM	CS	CMS
Lavoie et al. (1988)	√		NA	(DPN)	SC	Min pairing cost.	Continuous relaxation and Column generation approach	RL	Air France	√				
Anbil et al. (1991)	√		D	(DPN)	SP	Min pairing cost.	TRIP optimization system	RL	U.S.					
Ryan (1992)		√	M	-	Sp	Min rostering cost.	ZIP optimization package	RL	Air New Zealand					√
Graves et al. (1993)	√		D	TSN (FN)	SP	Min pairing cost.	Optimization system consists of generator and optimizer	RL	United Airlines					
Hoffman and Padberg (1993)	√		NA	NA	SP	Min pairing cost.	Branch-and-cut approach	RL	-	√				
Barnhart et al. (1995)	√		NA	(DPN)	SP	Min pairing and deadhead cost.	Developed algorithm	RL	-	√				
Chu et al. (1997)	√		D	-	SP	Min pairing cost.	Graph based branching heuristic	NA	-					
Day and Ryan (1997)		√	W	-	SP	Min the rostering cost.	ZIP optimization package	RL	Air New Zealand					√
Desaulniers et al. (1997a)	√		W	TSN (FN)	MCNF	Min pairing cost.	Branch-and-bound algorithm based on Dantzig-Wolfe decomposition principle	RL	Air France	√				
Vance et al. (1997)	√		D	(DPN)	DP	Min duty period and pairing costs.	Linear programming relaxation and dynamic column generation	RL	-	√				
Gamache et al. (1998)		√	M	-	SP	Max the schedule score of crew member.	Column generation embedded on a branch-and-bound-tree	RL	Air Canada				√	
Gamache et al. (1999)		√	M	-	SP	Min cost of uncovered pairing.	Column generation approach	RL	Air France					√

Lučic and Teodorovic (1999)		√	M	-	NA	Min average and absolute flight time deviation	Developed algorithm based on pilot-by-pilot heuristic algorithm and simulated annealing technique	RL&G	-				√	
Dawid et al. (2001)		√	M	-	SP	Max the total utility value.	SWIFTROSTER algorithm	RL	European					
Klabjan et al. (2001)	√		W	TSN (FN)	MCNF	Min pairing cost and regularity penalty.	Developed algorithm	RL	United Airlines	√				
Fahle et al. (2002)		√	M	-	SP	Min rostering cost.	Constraint programming based column generation approach	RL	European				√	
Yan and Chang (2002)	√		W	(DPN)	SP	Min the total crew cost.	Column generation approach	RL	Taiwan	√			√	
Ehrgott and Ryan (2002)	√		NA	-	SP	Min pairing cost and non-robustness.	1st: Weighted sum method 2nd:Ɛ-constraint method	RL	-		√			
Cappanera and Gallo (2004)		√	M	(DPN)	MCNF	Min number of uncovered activities.	CPLEX 7.0 (ILOG 2000)	RL	Italian					√
Schaefer et al. (2005)	√		D	NA	SP	Min expected crew pairing cost.	Push-back recovery heuristic	G	-			√		
Yen and Birge (2006)	√		D	TSN (FN)	SP	Min pairing cost.	Flight-pair branching algorithm	RL	Air New Zealand		√	√		
Guo et al. (2006)	√	√	NA	TSN (FN)	NF	Min overnight and compensation costs.	Rostering heuristic	RL	European					
Shebalov and Klabjan (2006)	√		D	TSN(FN)	SP	Max the number of move-up crews.	Delayed column generation and Lagrangian relaxation	RL	-		√			
Zeghal and Minoux (2006)	√	√	W&M	-	ILP	Min total number of extra flight credits.	1st: CPLEX 6.0.2 2nd: Developed heuristic based on a rounding strategy embedded in a partial tree search procedure	RL	Tunis Air				√	

Achour et al. (2007)		√	M	-	SP	Max the schedule score of crew member.	Exact approach based on column generation	RL	North American carrier.				√	
Souai and Teghem (2009)	√	√	D	-	SP	Min total cost and deviation.	1st: Hybrid genetic algorithm 2nd: Two local search heuristic[Legality Repair Heuristic and Feasibility Repair Heuristic]	RL	Air-Algérie				√	
Tekiner et al. (2009)	√		NA	TSN (FN)	SP	Max number of desired pairing.	ILOG OPL Studio5.5/CPLEX 11.0	RL	Local Airline in Turkey		√		√	
(Maenhout and Vanhoucke, 2010)		√	M	(DPN)	SP	Min total penalty cost.	1st:Hybrid scatter search heuristic 2nd: Exact branch-and-price procedure 3rd: Steepest descent variable neighbourhood search.	RL	Brussels Airlines					√
Deng and Lin (2011)	√		D&W	TSN (FN)	TSP	Min pairing, rest, and under utility costs.	Ant colony optimization algorithm	RL	-	√			√	
Saddoune et al. (2011)	√	√	M	TSN (FN)	SP	Min schedule and pilot penalty cost.	Column generation and dynamic constraint aggregation method	RL	North American				√	
Muter et al. (2013)	√		D&W	TSN (FN)	SC	Min pairing and deadhead costs.	Column generation approach	RL	Local Airline in Turkey		√		√	

Problem tackled: crew pairing problem (CPP) or crew rostering problem (CRP). Planning horizon: daily (D), weekly (W), or monthly (M). Network: duty period network (DPN) or time-space network (TSN) =flight network (FN). Model formulation: network flow or multi-commodity network flow (MCNF), set-partitioning (SP), set covering (SC), traveling salesman problem (TSP) or Duty period (DP). Used Data: real life (RL) or generated (G). Other features: basic crew pairing model (BCPM), robust model (RM), stochastic model (SM), cockpit scheduling (CS), cabin member scheduling (CMS).

Table 6: Characteristics of integrated schedule planning models.

Author/s (year)	Problem Tackled				Planning horizon	Network	Model formulation	Objective function	Solution procedure	Computational study	
	FSP	FAP	AMRP	CPP						Data	Airline
Clarke et al. (1996)		√	√	√	D	TSN	ILP	Min the assignment cost	Developed algorithm	RL	U.S
Yan et al. (1997)	√	√			W	TSN	NF	Min fleeting and flight scheduling cost.	Lagrangian based algorithm, subgradient method, the network simplex method and a Lagrangian heuristic	RL	Taiwan
Barnhart et al. (1998)		√	√		W	CN	SP	Min maintenance cost of selected strings	Branch and price, and cut algorithm	G	-
Ioachim et al. (1999)	√	√			W	CN	MCNF	Min the assignment cost	Linear relaxation by Dantzig-Wolfe decomposition and column generation embedded within a branch-and-bound method	RL	European
Cordeau et al. (2001)			√	√	D	TSN	MILP	Min routing and crew cost.	Benders decomposition, column generation, and branch-and-bound heuristic.	RL	Canadian
Yan and Tseng (2002)	√	√			NA	TSN	MCNF	Min the fleeting and passenger cost	algorithm based on Lagrangian relaxation, a sub-gradient method, the network simplex method, the least cost flow augmenting algorithm and the flow decomposition algorithm	RL	Taiwan
Klabjan et al. (2002)			√	√	D	TSN	SP	Min pairing cost.	Developed algorithm	RL	United Airlines
Cohn and Barnhart (2003)			√	√	NA	TSN	SP	Min pairing cost.	Branch and price approach	NA	-
Lohatepanont and Barnhart (2004)	√	√			D	NA	MILP	Max revenue minus operating and spill cost plus recaptured revenue	Developed algorithm based on column and row generation, and branch-and-bound	RL	U.S.

Mercier et al. (2005)			√	√	D	TSN	MILP	Min crew, routing and penalty costs.	Benders decomposition methods	RL	-
Mercier and Soumis (2007)	√		√	√	D	NA	MILP	Min routing and crew cost.	Benders decomposition method with a dynamic constraint generation	RL	-
Sandhu and Klabjan (2007)		√		√	D	TSN	MILP	Max fleet revenue minus crew cost.	1st : combination of Lagrangian relaxation and column generation 2nd : Benders decomposition approach	RL	U.S.
Gao et al. (2009)		√		√	NA	TSN	MILP	Max fleet profit minus crew and penalty cost.	ILOG CPLEX 9.0	RL	U.S.
Haouari et al. (2009)		√	√		W	CN	MCNF	Min assigning and routing cost	Network flow-based heuristic	RL	Tunis Air
Sherali et al. (2009)	√	√			NA	NA	MILP	Max the revenue.	Benders' decomposition method	RL	U.S.
Weide et al. (2010)			√	√	W	TSN	SP	Min routing, crew, and crew penalty cost.	Developed Algorithm	RL	-
Zeghal et al. (2011)		√	√		W	TSN	SP	Max net profit.	Tailored optimization-based heuristics	RL	Tunis Air
Haouari et al. (2011)		√	√		W	TSN	SP	Min the assigning and deadhead cost.	1st: Benders decomposition 2nd: Branch-and-price	RL	Tunis Air
Liang and Chaovalitwongse (2012)		√	√		W	TSN	NF	Max the profit	1st:Diving heuristic 2nd: CPLEX callable library version 12.1	RL	U.S.
Pita et al. (2012)	√	√			D	NA	MILP	Max the profit.	Xpress with the optimizer version 20.00.11 (FICO 2009)	RL	TAP Portugal
Sherali et al. (2013)	√		√		D	CN	MILP	Max the net profit.	Reformulation-linearization technique and benders' decomposition-based method	RL	United Airline
Cadarso and Marín (2013)	√	√			D	NA	MCNF	Max the profit.	-	RL	Spanish

Dunbar et al. (2014)			√	√	D	CN	MILP	Min total delay propagation cost.	Re-timing heuristic	RL	-
Díaz-Ramírez et al. (2014)			√	√	D	CN	SP	Min routing, pairing and crew deadhead cost.	Developed Algorithm	RL	Latin American
Salazar-González (2014)		√	√	√	D	CN	MILP	Min fleeting, and routing and crew costs.	Developed Algorithm	RL	Canary Island
Shao et al. (2015)		√	√	√	D	CN	NLMIP	Max overall profit	Accelerated benders decomposition approach	RL	U.S.
Gürkan et al. (2016)	√	√	√		D	CN	NLMIP	Min spill cost, fuel consumption, and CO_2 emissions	1st: discretized approximation and cruise speed control algorithm. 2nd: mutli-stage triplet search algorithm.	RL	U.S.
Dong et al. (2016)	√	√			D	TSN	MCNF	Min aircraft operating cost	Relaxation heuristic algorithm	RL	Chinese carrier
Cacchiani and Salazar-González (2016)		√	√	√	W	CN	MILP	Min weighted sum of number of aircraft routes, number of crew pairing, and waiting time of crews between flights	1st: path-path method 2nd: arc-path method	RL	Canary Island

Problem tackled: flight scheduling problem (FSP), fleet assignment problem (FAP), aircraft maintenance routing problem (AMRP), or crew pairing problem (CPP). Planning horizon: daily (D) or weekly (W). Network: connection network (CN) or time-space network (TSN). Model formulation: network flow (NF), multi-commodity network flow (MCNF), set-partitioning (SP), mixed integer linear programming (MILP) or non-linear mixed integer programming (NLMIP). Used Data: real life (RL).