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Robust integrated maintenance aircraft routing and crew pairing

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ABSTRACT

Given a daily flight schedule and a set of aircraft fleets, the integrated aircraft routing and crew scheduling problem requires finding a maintenance feasible set of aircraft routes and crew pairings such that each individual flight is covered by exactly one aircraft route and one crew pairing. Although these problems are interdependent, they have been traditionally solved sequentially, where the aircraft routing problem, which is solved first, defines a set of periodic aircraft rotations that impose some restrictions on short connections that are subsequently accommodated by the crew pairing problem. A major drawback of this sequential approach is that it ignores most of the interdependencies between the two problems. In particular, it fails to build robust solutions that are resilient to unpredictable disruptions (like adverse weather, aircraft breakdowns, etc.) that translate into delayed and canceled flights. In this paper, we propose an integrated robust model that incorporates the aircraft routing and crew pairing problems within a single framework that aims at generating aircraft routes that are both robust and cost-effective while accommodating technical constraints. A peculiar feature of the proposed model is that it includes a polynomial number of variables and constraints. We solve the resulting integrated model by using a general-purpose solver. Computational results obtained by using data from major airlines demonstrate the benefits of the proposed robust model.

1. Introduction

On January 1, 1914, the world witnessed the first scheduled passenger airline service linking St. Petersburg and Tampa, Florida. Although, this line lasted three months only, it paved the way for today's air transport prosperity. Since then, the use of commercial aviation has grown more than seventy-fold, an achievement that is unmatched by any other major form of transport. A disposal income and living standards, reduced air travel costs, deregulation and globalization enlarged the demand for air services, all of these and other factors foreshadow a perennial appeal of the sector.

A proper appraisal of the economic importance of air industry requires highlighting its contributions to the global business. Actually, in 2016, airlines worldwide carried upward 3.6 billions of passengers and 53 million tones of freight. It supported a total of 62.7 million jobs globally, where 9.9 million of them are direct jobs. The total economic impact of the worldwide aviation industry accounted for $ 2.7 trillion, roughly 3.5% of world's gross domestic product (GDP).[1] Actually, the aviation industry contributes to the world GDP more than any other sectors such as the pharmaceuticals, automotive and the textiles industries, and it is more than half the size of the global financial services industry.

In the current context of volatile markets and shrinking prices, airlines compete by using various Operations Research (OR) models and algorithms to neatly manage their complex operations and processes (Barnhart et al. (2003)). In this regard, typical airline processes that intensively use OR techniques include:

- Schedule design (Warburg et al. (2008), Jiang and Barnhart (2009) and Eltoukhy et al. (2017)): This planning process requires determining which cities to fly to and at what times so as to generate a schedule that offers the highest potential revenue. The generated schedule constitutes the basis of the airline operations.
- Fleet assignment (Sherali et al. (2006) and Dožić and Kalić (2015)): This planning process deals with assigning aircraft types, each having a different capacity (number of seats), to the scheduled flight legs, based on aircraft fleet sizes, operational costs, and expected revenues.

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[1] http://www.atag.org/facts-figures.html.

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- Aircraft routing (Lacasse-Guay et al. (2010) and Al-Thani et al. (2016)): This planning process includes the determination of the sequence of flight legs to be flown by each individual aircraft so as to cover each flight exactly once while satisfying maintenance requirements.
- Crew scheduling (Gopalakrishnan and Johnson (2005) and Kasirzadeh et al. (2015)): This planning process involves the assignment of qualified crews to each flight leg while satisfying numerous complex work rules.

These problems are typically solved sequentially, where the solution of one problem serve as an input for the following. Clearly, this divide-and-conquer strategy offers the significant advantage of considerably reducing the computational burden, but at the cost of producing suboptimal solutions. Nevertheless, over the last decade, several authors successfully addressed the foregoing problems in some integrated fashion (Shao et al. (2017)). The basic premise behind such approaches is to catch the interdependencies that exist between the various planning stages, and produce more cost-effective solutions.

A glaring fact in this context, is that optimized schedules are scarcely implemented as planned. The reason behind this paradoxical situation is that several random (uncontrollable) adverse incidents frequently disrupt scheduled flights. These disruptions are usually attributed to several causes such as aircraft breakdowns, air-traffic congestion, crew shortages, aircraft arriving late, and inclement weather conditions, etc., and translate into delayed and canceled flights, and thereby additional financial burden and profit loss. Actually, the number of disrupted flights has spiraled during the last years along with the air industry expansion. In this context, it has been reported that 18.58% of US airlines flights were delayed by more than 15 min in2016.[2]

The sizable expenses generated by flight delays are arguably straightforward to quantify, consisting of (1) cost of flights' operations (e.g. additional fuel and maintenance costs), (2) passengers' delay costs (including passengers' accommodation and meals), (3) crews' overtime payment, and (4) revenue losses that are incurred by, refleeting decisions, cancelled routes as well as passengers that are reaccommodated on different airlines (AhmadBeygi et al. (2008)). Cook and Tanner (2015) estimated that a 1 min of delay may cost up to €1.75 per passenger. It is noteworthy that these estimates downplay the cost of the damages inflicted to airlines' reputation, which is translated into loss of future business.

In response to these challenges, airlines are seeking to implement novel tools and techniques for building robust schedules that are less vulnerable to unpredictable disruptions when they occur (see Chtourou and Haouari (2008), Ben Ahmed et al. (2017b) and Ladier and Alpan (2016) among others). In this context, robustness can be achieved through embedding a schedule with specific patterns, that allow it to exhibit (*i*) *resilience* (or, *flexibility*), which is defined as the ability to easily recover after a disruption, or (*ii*) *stability* which refers to the ability to absorb or mitigate flight delays with limited impact on the downstream flights. During the last, the issue of designing robust airline schedules has been intensely investigated by many authors. We refer to Muter et al. (2013), Cadarso and Marín (2013), Jamili (2016), Ben Ahmed et al. (2017a) and Yan and Kung (2018), for the most recent ones.

In this paper, we address the robust integrated aircraft routing and crew pairing problem (RIARCP). This model achieves the integration of two stages: it requires simultaneously determining periodic maintenance feasible aircraft routes and crew pairings. In contrast to previous integrated models, our model includes a polynomial number of variables and constraints. Therefore, it can be directly solved using a general-purpose solver without requiring the implementation of sophisticated branch-and-price or branch-and-cut algorithms. Furthermore, a major goal of our model is to produce a cost-efficient robust integrated solution. In this case, robustness is achieved through embedding two effective modeling features: (*i*) connections having very short buffer times are aggressively avoided both in aircraft routes and crew schedules as well, and (*ii*) connections that are simultaneously covered by aircraft routes and crew schedules are promoted. In so doing, a delay that occurs on a given flight has a limited chance to propagate to downstream flights and thereupon cause severe disruptions. Therefore, our model aims at deriving schedules that are less sensitive to reactionary delays (i.e. delays caused by late arrival of aircraft or crew from previous flight). It is well-documented that reactionary delays represent the major cause of delays[3] that have been plaguing airlines worldwide, and whose impact is more dramatic. As shown in Table 1 below, because of the so-called snowball effect, a reactionary delay can be, under specific circumstances, up to seven times greater in magnitude than the source delay.

More precisely, we make the following contributions:

- We propose a polynomial-size mixed-integer nonlinear programming model for the robust integrated aircraft routing and crew pairing problem. To the best of our knowledge, this is the first contribution in this regard. Our model builds upon the aircraft routing model of Haouari et al. (2013) and the crew pairing model of Zeghal Mansour et al. (2018). We apply the Reformulation-Linearization Technique (RLT) of Sherali and Adams (1990, 1994) to provide an equivalent lifted linear mixed-integer programming formulation.
- We assess the empirical performance of the proposed model through an extensive computational study that was carried on realistic instances based on data provided by major airlines. In particular, we provide evidence that instances with up to 336 flights, and 95 aircraft can be optimally solved within reasonable CPU times.
- We evaluate the performance of the derived robust solution, using a Monte-Carlo simulation study, and we show that our solutions substantially outperform solutions produced by a non-robust approach.

The remainder of this paper is organized as follows. In Section 2, we review the literature pertaining to integrated airline operations models. In Section 3, we present a formal problem description along with the associated underlying aircraft and crew graphs. In Section 4, we provide a detailed description of the proposed integrated model. This model is first introduced as a nonlinear mixed-integer program. Next, the Reformulation-Linearization Technique (RLT) is employed to derive an equivalent linear model. In Section 5, we report the results of our computational experiments that were carried out on realistic data from major airlines. Finally, in Section 6, we provide some concluding remarks and outline directions for future research.

2. Literature review

Since the pioneering applications of Operations Research in the airline industry in the early 1960s, it has been realized that solving the integrated aircraft routing and crew pairing problem is a cumbersome task that goes well beyond the capabilities of the optimization technology that was available at these times. However, prompted by the joint development of sophisticated optimization techniques, speeded-up computers, together with enhanced commercial optimization solvers, several approaches have been proposed during the last 15 years in the literature to address numerous variants of integrated aircraft routing and crew pairing models. In this section, we shed light on the most

[2] https://transtats.bts.gov/OT_Delay/OT_DelayCause1.asp?pn=1.

[3] Understanding the Reporting of Causes of Flight Delays and Cancellations, http://www.bts.gov/help/aviation/html/understanding.html.