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Airline crew pairing with fatigue: Modeling and analysis

Burak C. Yildiz, Fatma Gzara, Samir Elhedhli [*]

Department of Management Sciences, University of Waterloo, 200 University Avenue West, Waterloo, Ontario, Canada

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ABSTRACT

Crew fatigue is one of the main causes of airline accidents. Regulatory authorities such as the Federal Aviation Agency constantly introduce new fatigue regulations, often in the form of hard constraints on the length of duty and rest periods. The complex nature of travel-related fatigue, however, makes it difficult to account for it indirectly through such constraints. Recent studies show that fatigue depends on human factors such as the homeostatic process and the circadian body clock as well as time-zone differences. In this work, we explicitly account for fatigue in crew pairing optimization through the Three Process Model of Alertness, one of the most comprehensive fatigue models available in the literature. We provide a mathematical model for the crew pairing problem that incorporates fatigue and solve it using a column generation approach. Numerical analysis on two real data sets reveals that the proposed approach is able to reduce the crew fatigue levels substantially with minimal impact on cost. In particular, it is shown that hard constraints on fatigue may still lead to high fatigue levels and that jet-lag and time-zone differences have a major impact. The results of the tests also show that some of the rules and regulations in practice may be omitted if the fatigue is accounted for directly.

1. Introduction

Although air transportation is one of the fastest and safest mode of transportation, in the rare event of an accident, losses - both humanitarian and financial - are devastating (Evans, 2003; Evans, 2003; Loeb et al., 1994). According to Caldwell (2005), the total cost of a single major civil aviation accident can exceed $500 million. Several investigations have identified fatigue-related factors as major causes of aviation accidents. According to Goode (2003), the number of accidents per pilot is proportional to the length of his/her duty periods and directly correlates with his/her fatigue level. Furthermore, using official data, Caldwell (2005) shows that in at least 4–8% of aviation accidents, fatigue is involved. For example, in the "Flight CRX 3597" accident, the Swiss Aircraft Accident Investigation Bureau found that fatigue has negatively affected the pilot's ability to concentrate and make appropriate decisions and impaired his capacity to analyze complex processes (BEAA, 2001). According to the US National Transportation Safety Board, more than 300 fatalities are attributed to fatigue, some of which are direct causes of long duty periods, circadian disruptions, and sleep loss (Avers and Johnson, 2011).

In light of the direct relation between crew fatigue and accidents, the U.S. Federal Aviation Administration (FAA) and similar regulatory authorities are constantly introducing and enforcing new rules and regulations to implicitly account for fatigue. These rules are often hard constraints on the length of duty periods, the minimum break time between duties, etc. Up until now, the research literature has sought to model existing regulations; which are hard constraints. The research

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[*] Corresponding author.
E-mail address: elhedhli@uwaterloo.ca (S. Elhedhli).

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literature has not sought to model fatigue directly, which would require more complex models. (Suraweera et al., 2013) uses a constraint learning system based on machine learning to infer minimum rest crew scheduling constraints based on historical data.

Although traditional models include these strict rules, judging by the increasing focus on fatigue-related safety, it is clear that the current rules are not sufficient to model the complex nature of fatigue. This paper is an attempt to model fatigue explicitly and incorporate it in crew pairing optimization. We present a model that captures the trade-off between operating costs and fatigue levels by explicitly accounting for fatigue in the objective function. Instead of assuming that fatigue is a function of duty periods, we use a comprehensive model to account for circadian body clock, time-zone differences, and homeostatic processes.

The airline crew pairing problem is the first step in a sequential two-step process in crew scheduling. The second step is crew rostering. The crew scheduling problem is tackled after an airline generates schedules, makes fleet assignment, and decides on maintenance routing. The airline crew pairing problem decomposes by fleet type, because cockpit crews are usually qualified to operate only one fleet type.

Barnhart et al. (2003) give a comprehensive survey of airline crew scheduling. They describe the terminology used in the industry, examine different cost structures, and provide a set partitioning formulation for the problem. Denoting the set of flight legs by L and the set of all possible feasible pairings by P, and using binary decision variables θ_p that is equal to 1 if pairing p is selected and 0 otherwise, the set partitioning formulation for the airline crew pairing problem is:

$$[P] : \min \quad \sum_{p \in P} c_p \theta_p$$

$$\text{s.t.} \quad \sum_{p \in P} a_{ip} \theta_p = 1 \quad i \in L \tag{1}$$

$$\theta_p \in \{0, 1\} \quad p \in P, \tag{2}$$

where a_{ip} is 1 if pairing p contains flight i. Column generation is commonly used to solve problem [P], where the pairing generation subproblem is a Resource Constrained Shortest Path (RCSP) problem. The subproblem can be solved using a label setting algorithm by considering the label of a node as a cost-resource vector (Desaulniers et al., 1997; Desaulniers et al., 1998 and Desrosiers et al., 1995). The subproblem includes constraints on the time spent away from base and minimum/-maximum duty and flight breaks that implicitly account for fatigue. In this work, however, we try to model fatigue explicitly.

According to Brown (1994), fatigue is defined as the “Reduced capacity to perform mentally or physically taxing work, or the subjective situation in which the person cannot perform a task anymore, and it results from inadequate sleep, circadian rhythm disruptions and/or time spent at work”. Caldwell (2005) and Graeber (1988) showed that the reason that domestic and international pilots experience fatigue is largely because of sleep irregularities, night flights, early duty starts, and long duty periods. Furthermore, Graeber et al. (1986) argued that multiple time zone changes that are experienced during long flights can lead to the desynchronization of the circadian body clock. This desynchronization results from the difficulty of the 24-h sleep/wake cycle to swiftly readjust to the rapid change of “time givers”, such as sunlight, that is caused by multiple time zone changes (Arendt et al., 2000 and Graeber, 1988). This desynchronization is shown to result in sleep disruption and decreased alertness (Caldwell and Caldwell, 2003 and Gander et al., 1998).

In a survey conducted by Bourgeois-Bougrine et al. (2003), international pilots identified night flights (59%) and jet-lag (45%) as the primary causes of fatigue. They also confirmed that fatigue results in reduced attention and increased difficulty in accomplishing certain tasks. A detailed literature on fatigue is given by Petrilli et al. (2006).

Although regulations are in place to minimize crew fatigue, Caldwell (2005) and Dawson and Fletcher (2001) argue that current fatigue-related regulations take duty time and sleep into account, but fail to account for the sleep levels before the start of a duty. According to Petrilli et al. (2006), higher levels of fatigue have been reported by commercial airline pilots at the end of international flights and the amount of sleep obtained in the 24 h prior to the end of the flights seems to be a significant indicator of fatigue. A study similar to Ahlstrom et al. (2013) to assess pilots’ fitness for duty prior to each flight will help clarify the severity of fatigue that pilots experience.

The literature is rich with crew pairing formulations that include the strict rules and regulations provided by aviation agencies (e.g. Desrosiers et al., 1995; Desaulniers et al., 1997; Lu and Gzara, 2014, Gürkan et al., 2016). In a report by Jeppesen, it was shown that current aviation rules by themselves are ineffective to account for fatigue (Olbert and Klemets, 2011). In a report by Romig and Klemets (2009), Boeing and Jeppesen work on a fatigue measuring scheme. It is not clearly stated how they account for fatigue, but using an interface called CAPI (Common Alertness Prediction Interface), they were able to measure the fatigue level for flights and use it at the pairing selection stage. To our knowledge, there is no academic work that tries to explicitly tackle the fatigue issue in airline crew pairing. This work is an attempt in that direction.

To explicitly account for fatigue in a mathematical model, a quantitative approach is needed. There are several published models to calculate the fatigue level of a person. The Three Process Model of Alertness (TPM) created by Åkerstedt and Folkard (1990) is a comprehensive model that calculates alertness recovered during sleep, alertness lost during wake, and the effect of the 24-h circadian body clock. Since its introduction, several extensions were introduced. Åkerstedt et al. (2007) provided another function to account for the effect of the 12-h circadian body clock. Åkerstedt et al. (2008) provided a brake function that modifies the alertness recovery during sleep. According to this function, the sleep is broken into two parts: deep sleep and normal sleep. The recovery rate during deep sleep is higher than that during normal sleep. There is also