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Multi-stage airline scheduling problem with stochastic passenger demand and non-cruise times

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A B S T R A C T

We propose a three-stage stochastic programming model which determines flight timing, fleeting and routing decisions while considering the randomness of demand and non-cruise times. Our model differs from the existing two-stage stochastic models by considering not only flight timing and potential passenger demand, but also expected operational expenses, such as fuel burn and carbon emission costs. We include aircraft cruise speed decisions to compensate for non-cruise time variability so as to satisfy the time requirements of the passenger connections. We handle nonlinear functions of fuel and emission costs associated with cruise speed adjustments by utilizing mixed integer second order cone programming. Because the three-stage stochastic model leads to a large decision tree and can be very time-consuming to solve optimally, we suggest a scenario group-wise decomposition algorithm to obtain lower and upper bounds for the optimal value of the proposed model. The lower and upper bounds are obtained by solving a number of group subproblems, which are similar to proposed multi-stage stochastic model defined over a reduced number of scenarios. We suggest a cutting plane algorithm, along with improvements, to efficiently solve each group subproblem. In the numerical experiments, we provide a significant cost savings over two-stage stochastic programming and deterministic approaches.

1. Introduction

At major airports, air traffic congestion may cause significant delays in flight departures and arrivals, in turn disrupting aircraft connections and passenger itineraries. According to the U.S. Department of Transportation (BTS, 2017c), around 18% of flights were delayed in 2016. Almost 29% of delays occurred due to the air carrier, 36% were due to the aircraft arriving late, and 31% were due to the National Aviation System. Only 4% of delays were due to heavy weather conditions and security issues. In 2010, FAA/Nextor (2017) reported that the cost of all US air transportation delays in 2007 totalled $31.2 billion. $16.7 billion, or about half of the total cost was incurred from the extra cost of the passengers' longer travel times. For airlines, increased expenses for crew, fuel, and maintenance expended $8.3 billion. Accordingly, and especially with consideration of a highly competitive market, it is crucial for airlines to manage their flights, aircraft and crews efficiently to minimize operational costs. Airlines are willing to seek additional advanced solution techniques that allow them to make decisions jointly, thus producing solutions which provide reliable performance despite the uncertainties involved in flight operations.

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The problem of airline scheduling has been disaggregated into different stages such as schedule design, fleet assignment, aircraft routing and crew scheduling. Accordingly, a sequential planning approach has traditionally been employed. The first step, known as schedule design, is a strategic planning problem usually requiring reconciliation at least a year in advance of departures. Schedules of flights with predetermined origins, destination airports and flight departure and arrival times are generated by considering potential passenger demand, fleet and crew resources. Following completion of this first stage, airline engineers can begin the fleet assignment problem: here, aircraft types, each having a different seat capacity, are assigned to flight legs based on their equipment capabilities, availabilities and operational expenses. However, because of the stochastic nature of passenger demand, assigning the right type of aircraft to each leg is a challenging problem to solve prior to departures. Realized demands may either exceed or fall short of the capacity of assigned aircraft type, resulting in loss of profit and customer goodwill. Following fleet assignment, a minimum cost route must be determined for each aircraft while satisfying the maintenance requirements.

As suggested by Yan et al. (2008), passenger demand fluctuations have to be considered in modeling the scheduling problem. In recent years, a growing literature has focused on the fleeting problems with uncertain demand. Listes and Dekker (2005) use a two-stage stochastic programming model to determine an optimal airline fleet composition (i.e., number of aircraft contained in each fleet type) to provide a re-fleeting process. In the second stage, they assign aircraft to each leg under each demand scenario by allowing swapping. One of the main drawbacks of stochastic programming is that the consideration of many scenarios simultaneously may lead to large decision trees significantly lengthening the computation time to solve the overall model. Therefore, for computational tractability, Listes and Dekker (2005) use a scenario aggregation approach. Sherali and Zhu (2008) analyze the several demand scenarios in their two stage stochastic fleet assignment model. In the first stage, they assign aircraft families having the same crew requirement with different aircraft types to flight legs. Given the assignment of such aircraft families, they subsequently assign aircraft types within the allotted family to each leg under each demand scenario. In their study, Sherali and Zhu develop a Benders' decomposition-based solution framework. However, they were unable to optimize real problem instances for United Airlines within a 25-hour time limit. Cadarso and de Celis (2017) propose a mathematical model to improve base schedules in terms of timetable and fleet assignments while accounting for passenger demand and operating conditions uncertainty. However, they do not consider the integration of aircraft routing problem along with the fleeting decisions, which may provide more economical solutions and prevent some incompatibilities between the decisions.

Aside from passenger demand fluctuations, airport congestion is another crucial uncertainty involved in flight times. These uncertainties are not included in any planning stages of a deterministic approach, despite the disruptions that flight delays propagate through the network, ultimately affecting a large scale of aircraft routes and passenger itineraries. Therefore, Yen and Birge (2006) consider the effect of random disruptions to develop a robust schedule which can better withstand delays. In their two-stage stochastic integer programming formulation, in the first-stage, they determine pairings of a round-trip itinerary that a crew member might fly; in the second stage, they consider several disruption scenarios to determine actual departure and arrival times. Sohoni et al. (2011) propose two stochastic models which incorporate block time uncertainty into the schedule development process. More recently, Dunbar et al. (2014) incorporate delay scenarios within the aircraft routing and crew pairing problems. In order to minimize delay propagation, they adjust flight departure times, in turn providing more slack over critical connections and drawing excess slack from remaining connections. Chiraphadhanakul and Barnhart (2013) desire slacks in robust schedule to absorb delays. Ahmadbeygi et al. (2010) propose a method to minimize the delay propagation by redistributing the existing slack in the flight schedule. Liang et al. (2015) also extend the robust weekly aircraft maintenance routing problem for the operational tail assignment model to minimize the total expected propagated delay.

An alternative way of ensuring on-time connections is to control aircraft speed as discussed in Cook et al. (2009). Bertsimas et al. (2010) control aircraft speed through adjustments in the time spent in each en route sector while deciding on an optimal combination of flow management actions including ground holding, rerouting and airborne holding. Sherali et al. (2006) emphasize the sensitivity of airline optimization decisions to fuel burn. More recently, Şafak et al. (2017) consider the fuel burn and CO_2 emission costs associated with cruise speed adjustments to ensure the passenger connections in their integrated aircraft-path assignment and robust scheduling problem. Gürkan et al. (2016) also include aircraft cruise speed decisions in an integrated airline scheduling, aircraft fleeting and routing problem. The major difficulty of including cruise time as a decision variable in their models is the consideration of nonlinear functions of fuel burn and carbon emissions. To handle this nonlinearity, they utilize the mixed-integer second order cone programming as discussed in Aktürk et al. (2014). In addition to aviation sector, Yang et al. (2016) and Haahr et al. (2017) provide significant savings in the total tractive energy consumption by optimizing train speed profiles. Furthermore, in maritime transportation, He et al. (2017) and Fagerholt et al. (2015) optimize the speed to minimize the fuel emissions. In the context of road transportation, Bektaş and Laporte (2011) propose a pollution routing problem to find the optimal routes and speeds to minimize the total costs of fuel consumption and emissions.

None of the discussed approaches consider the interplay between schedule design, fleet assignment and aircraft routing, and cruise time decisions in an uncertain environment. Let us consider a situation with high uncertainty in non-cruise times due to airport congestion. On the one hand, airlines may choose to set a higher cruise speed to guarantee the minimum time requirements for passenger connections. Since speeding up the aircraft results in additional fuel burn and carbon emission costs, assigning a fuel efficient but smaller aircraft may be preferable. However, such an assignment may spill some of the passengers because of the insufficient seat capacity of the aircraft. Thus, passenger demand needs to be taken into account