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Air traffic flow management under uncertainty using chance-constrained optimization

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ABSTRACT

In order to efficiently balance traffic demand and capacity, optimization of Air Traffic Flow Management (ATFM) relies on accurate predictions of future capacity states. However, these predictions are inherently uncertain due to factors, such as weather. This paper presents a novel computationally efficient algorithm to address uncertainty in ATFM by using a chance-constrained optimization method. First, a chance-constrained model is developed based on a previous deterministic Integer Programming optimization model of ATFM to include probabilistic sector capacity constraints. Then, to efficiently solve such a large-scale chance-constrained optimization problem, a polynomial approximation-based approach is applied. The approximation is based on the numerical properties of the Bernstein polynomial, which is capable of effectively controlling the approximation error for both the function value and gradient. Thus, a first-order algorithm is adopted to obtain a satisfactory solution, which is expected to be optimal. Numerical results are reported in order to evaluate the polynomial approximation-based approach by comparing it with the brute-force method. Moreover, since there are massive independent approximation processes in the polynomial approximation-based approach, a distributed computing framework is designed to carry out the computation for this method. This chance-constrained optimization method and its computation platform are potentially helpful in their application to several other domains in air transportation, such as airport surface operations and airline management under uncertainties.

1. Introduction

The goal of Air Traffic Flow Management (ATFM) is to allocate airspace resources such that the balance between capacity and demand is maintained, subject to both en-route and airport capacity constraints. Airport and airspace sector capacities are greatly influenced by weather conditions such as fog, snow, wind and reduced visibility. These severe weather conditions may reduce both airspace and airport capacity such that the demand and supply situation of ATFM is made worse. According to Sridhar et al. (2008), severe weather has been identified as the most important causal factor for traffic delays in the United States. Moreover, the weather forecast brings uncertainty into capacities, which also poses a significant challenge to ATFM. Strategic traffic flow management decisions made under uncertainty can cause nationwide severe congestion in the

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National Airspace System (NAS). This fact motivates the need for stochastic optimization algorithms for ATFM that account for capacity uncertainty.

In the past three decades, the flow management problem in air transportation has been studied by many researchers in order to address air traffic congestion. The first effort dates back to 1987, when Odoni was among the first to propose the mathematical formulation of ATFM (Odoni, 1987). Later, Bertsimas and Stock Patterson proposed a binary integer programming formulation that considered both airspace and airport capacities, known as the BSP model (Bertsimas and Patterson, 1998). The description of the state of aircraft is based on the trajectory of individual aircraft; therefore, BSP is a Lagrangian model. A limitation of Lagrangian models is that the dimension of the model is related to the number of aircraft involved in the planning time horizon. The BSP model is proved to be non-deterministic polynomial-time (NP) hard by deriving the equivalent job-shop scheduling problem (Bertsimas and Patterson, 1998). Subsequently, Bertsimas presented several extensions of the BSP model to account for other features, such as rerouting (Bertsimas et al., 2008, 2011; Bertsimas and Patterson, 2000).

To overcome the computational limitation of the Lagrangian models, the Eulerian model of ATFM was proposed (Menon et al., 2004), which is inspired by the Daganzo Cell Transmission Model (Daganzo, 1994, 1995). Since the Eulerian approach spatially aggregates the air traffic, its computational complexity does not depend on the number of aircraft, but only on the size of the network problem. Afterwards, an aggregate Eulerian-Lagrangian model was proposed to eliminate the splitting and diffusion problems of some Eulerian models by taking into account the origin-destination information of flights (Sun and Bayen, 2008; Cao and Sun, 2011). Moreover, the distributed algorithms for these aggregate models have also been proposed using the dual decomposition method (Sun et al., 2011; Wei et al., 2013).

Since weather conditions are difficult to predict and have a significant impact on capacities, considerable efforts have been made to address the capacity uncertainty. Due to the computational complexity of solving large-scale ATFM problems, most of the stochastic ATFM models are limited to optimizing flows into a single airport, which is known as the Single Airport Ground Holding Problem (SAGHP). As one of the first attempts, Richetta and Odoni formulated a stochastic integer programming model for the SAGHP (Richetta and Odoni, 1994). Subsequently, Ball et al. proposed a modified version for the same problem, which solves for an optimal number of planned arrivals of aircraft during different time intervals (Ball et al., 2003). Recently, Mukherjee and Hansen proposed a model that incorporated dynamic rerouting into SAGHP (Mukherjee and Hansen, 2007, 2009). In all of the aforementioned models, the uncertainty in capacities was represented through a finite number of scenarios arranged in a probabilistic decision tree. As time progressed, the branches of the tree were realized, resulting in better information about future capacities (Liu et al., 2008). Moreover, the techniques are developed to determine probabilistic capacity profiles and scenario tree forecasts from historical data (Liu et al., 2008). Unfortunately, the probabilistic scenario-tree approach suffers significantly from the practical difficulty of not knowing the exact distribution of the data to generate relevant scenarios. Furthermore, it generally becomes intractable quickly as the number of scenarios increases, thereby posing substantial computational challenges.

Besides the scenario tree method, robust optimization can also address decision-making under uncertainty. The robust optimization formulations of the ATFM problem was studied in Gupta and Bertsimas (2011) to address capacity uncertainties. However, the robust optimization may suffer from highly conservative solutions, since it is a consequence of the optimization over the worst-case realization of the uncertainty parameters. Consequently, there is an alternative method to incorporate probabilistic information called *Chance Constraints*. The idea is to constrain the chance of a constraint violation, given probabilistic information about future state disturbances. This is less conservative than the robust approach of constraining against the constraint violation for all possible disturbances. Currently, only one article has discussed the ATFM problem with Chance constraints (Clare and Richards, 2012), which is formed as a Mixed-Integer Linear Programming (MILP) model based on the BSP model. However, this MILP model uses the brute-force method to enumerate all possible capacity combinations. Thus the exponentially increased computational complexity prevents it from being applicable to large-scale problems in reality.

This paper presents a novel polynomial approximation-based chance-constrained optimization method to address uncertainty in ATFM, which could provide a computationally efficient algorithm. First, a chance-constrained model is developed based on a previous deterministic Integer Programming optimization model of ATFM to include probabilistic sector capacity constraints. Then, to efficiently solve such a large-scale chance-constrained optimization problem, a polynomial approximation-based approach is applied. The approximation is based on the numerical properties of the Bernstein polynomial, which is capable of effectively controlling the approximation error for both the function value and the gradient. Thus, a first-order algorithm is adopted to obtain a satisfactory solution, which is expected to be optimal. Numerical results are reported in order to evaluate the polynomial approximation-based approach by comparing it with the brute-force method. Moreover, since there are massive independent approximation processes in the polynomial approximation-based approach, a distributed computing framework is designed to carry out the computation for this method. This chance-constrained optimization method and its computation platform are potentially helpful in their application to several other domains in air transportation, such as airport surface operations and airline management under uncertainties.

The rest of this paper is organized as follows. Section 2 introduces the chance-constrained ATFM problem. Section 3 introduces a polynomial approximation-based approach to overcome the limitation of the brute-force method. The main algorithm based on the polynomial approximation-based approach is presented with computational complexity in Section 4. Section 5 demonstrates the parallel computing framework for the approximation-based approach. Section 6 evaluates the