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Characterization and prediction of air traffic delays

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A R T I C L E I N F O

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A B S T R A C T

This paper presents a new class of models for predicting air traffic delays. The proposed models consider both temporal and spatial (that is, network) delay states as explanatory variables, and use Random Forest algorithms to predict departure delays 2–24 h in the future. In addition to local delay variables that describe the arrival or departure delay states of the most influential airports and links (origin–destination pairs) in the network, new network delay variables that characterize the global delay state of the entire National Airspace System at the time of prediction are proposed. The paper analyzes the performance of the proposed prediction models in both classifying delays as above or below a certain threshold, as well as predicting delay values. The models are trained and validated on operational data from 2007 and 2008, and are evaluated using the 100 most-delayed links in the system. The results show that for a 2-h forecast horizon, the average test error over these 100 links is 19% when classifying delays as above or below 60 min. Similarly, the average over these 100 links of the median test error is found to be 21 min when predicting departure delays for a 2-h forecast horizon. The effects of changes in the classification threshold and forecast horizon on prediction performance are studied.

1. Introduction

Flight delays in the United States result in significant costs to airlines, passengers and society. The annual cost of domestic flight delays to the US economy was estimated to be $31–40 billion in 2007 (Ball et al., 2010; Joint Economic Committee, US Senate, 2008). Such high delay costs motivate the analysis and prediction of air traffic delays, and the development of better delay management mechanisms (Manley and Sherry, 2010; Ferguson et al., 2013; Glover and Ball, 2013; Delgado et al., 2013).

The large number of shared resources in the National Airspace System (NAS) together with aircraft, crew and passenger interdependencies result in the propagation of delays through the network (AhmadBeygi et al., 2008; Jetzki, 2009). The desire to maximize aircraft utilization reduces the time buffer between arrivals and departures, increasing the likelihood of delay propagation (AhmadBeygi et al., 2008). Increasing demand also decreases the ability of the network to absorb disruptions, making the network susceptible to large-scale delays. The study of network effects can help identify factors that mitigate or amplify delay propagation in the NAS.

Delay prediction has been the topic of several previous efforts. Jetzki (2009) studied the propagation of delays in Europe, with the goal of identifying the main delay sources. Tu et al. (2008) developed a model for estimating flight departure delay distributions, and used the estimated delay information in a strategic departure delay prediction model. Yao et al. (2010)

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focused exclusively on downstream delays caused by aircraft, cockpit and cabin crew connectivities. By contrast, Bratu and Barnhart (2005) focused on the impact of delays on passengers. Recently, Pyrgiotis et al. (2013) have considered delay propagation in a network of airports using a queuing model. Other prediction models (Klein et al., 2007; Klein et al., 2010; Sridhar and Chen, 2009) have focused on weather-related delays, and the development of a Weather Impacted Traffic Index (WITI). Xu et al. (2005) proposed a Bayesian network approach to estimating delay propagation. Using a system-level Bayesian network, the authors were able to capture interactions among airports. None of these prior approaches have investigated the role of a network delay state in predicting future delays. By contrast, the goal of this paper is to evaluate the potential of network-scale delay dependencies in developing delay prediction models.

Due to the existence of network effects, current delays in the NAS are expected to be a good indicator of the short term evolution of delays in the system. It is therefore useful to determine state variables that reflect the current situation, and use them to predict future delays. The models presented in this paper therefore attempt to predict future departure delays on a particular origin–destination (OD) pair by considering current and/or past delays in the network. The proposed prediction models will not capture delays that only affect a few aircraft (for example, mechanical delays). The objective of these models is *not* to predict individual flights delays, but instead to estimate the future network-related delay on a certain route. However, it is important to note that the models are evaluated using actual data containing all delays, including those that impacted only a few flights. The prediction models presented in this paper yield a better understanding of delay interactions between the different elements in the NAS. They also help assess how much of the future delay on a particular link can be explained by the current delay state of the network.

2. Problem definition

The main objective of this paper is to predict the departure delay on a particular link or at a particular airport, some time in the future. The departure delay of a link at time t is an estimate of the departure delay of any flight(s) taking off at time t, and flying on that link. For example, if the BOS-MCO departure delay state two hours from now is estimated to be 30 min, it means that the estimated departure delay for BOS-MCO flights taking off two hours from now is 30 min. Two types of prediction mechanisms are considered: *classification*, where the output is a binary prediction of whether the departure delay is more or less than a predefined threshold, and *regression*, where the continuous output is an estimate of the departure delay along the link.

2.1. Data sources

The results presented in this paper were obtained using data from the Aviation System Performance Metrics (ASPM) database (Federal Aviation Administration, 2012), for the two-year period beginning January 2007 and ending December 2008. The ASPM database provides detailed data for individual flights by phase of flight, airport weather data, runway configuration, and arrival and departure rates. The fields used in the analyses in this paper include the arrival and departure airports, the scheduled and actual gate-in times, the scheduled and actual wheels-off times, the flight carrier codes, and the aircraft tail number.

The individual flight data were processed to obtain a more robust aggregate delay estimate. A moving median filter, a low-pass filter, was used to obtain the delay states of airports and OD pairs. The delay state of a NAS element at time t refers to the median delay of all the flights that fall within a window of size W centered at time t. The window size, W, was set to two hours, and t was incremented in steps of one hour.

The raw data set spanned 2029 airports and 31,905 OD pairs, most of which averaged fewer than one flight a day. Since the analysis focused on network effects, only OD pairs with at least 10 flights per day on average were considered. Fig. 1 shows the resulting simplified network, which is composed of 112 airports and 584 OD pairs.

3. Characterization of the network delay state

The interdependencies among the different elements in the NAS and repetitive traffic patterns support the development of characteristic NAS delay states, that reflect the current situation at a network-level. These states are characterized both as a "snapshot" in time (i.e., the current delay patterns in the NAS), and in terms of temporal evolution (i.e., a characteristic type of day). In addition to yielding insights into system behavior, these delay states can be used as explanatory variables in prediction models.

3.1. Characteristic NAS delay states

The observed NAS departure delay at time t is a 584-dimensional vector, defined by the departure delay state of each link in the simplified network at time t. The 17,519 NAS departure delay observations were classified into a few typical NAS delay states using the k-means clustering algorithm (Hastie et al., 2009).

The k-means algorithm partitions the observations in the data set into k clusters so as to minimize the sum of distances within each cluster. In the case of departure delays, the centroids of each of the clusters represent the typical NAS delay