Journal of Air Transport Management 52 (2016) 35–41

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Analysis of short-term forecasting for flight arrival time

Myung Suk Kim

Sogang Business School, Sogang University, #1 Shinsu-dong, Mapo-gu, Seoul 121-742, Republic of Korea

ARTICLE INFO

Article history:
Received 18 June 2015
Received in revised form
9 November 2015
Accepted 17 December 2015
Available online 2 January 2016

Keywords:
Short-term forecasting
Air transport
Skew t distribution
Spline smoothing

ABSTRACT

We suggest various methodologies to provide short-term forecasting of flight arrival times. Flights arriving at Denver International Airport from various U.S. cities during 2010 are used for the model estimation, and the forecasting is applied to 2011 flights. Forecasting proceeds from the time at which a flight departs from an airport. Prediction models using the spline smoothing-based nonparametric additive techniques are applied and compared with benchmarks. We also provide a method for computing the probability of flight arrival time by fitting the skew t distribution to the models' residuals. Our empirical results indicate that a nonparametric additive model dominantly outperforms the other models considered. In terms of effect of predictor variables, departure delay time, scheduled airborne time, airlines, and weather conditions significantly improve forecasting accuracy, along with seasonal variables. In particular, departure delay time is the most important factor for substantially improving prediction performance.

1. Introduction

Modeling and forecasting flight departure and arrival time have been significant issues for both industry and academia. Recently, U.S. commercial airlines spent approximately $20 billion due to flight delays (Schumer and Maloney, 2008). Some rigorous research for costs to airlines from delays was carried out (Ball et al., 2010), and various attempts have been made to reduce costs. For example, Kaggle hosted the GE Flight Quest, at which more than 155 teams competed, using their algorithms to improve the prediction of delays (see https://www.gequest.com/c/flight).

Academic researchers also suggested various approaches to flight time modeling and forecasting. In the beginning, statistical linear or nonlinear type models were proposed and their prediction performances were evaluated. Xu et al. (2008) predicted positive and negative delays using multivariate adaptive regression spline models, which were useful in detecting a nonlinear relationship between the explanatory and response variables. Srivastava (2011) applied a linear regression model to predict taxi-out or taxi-out delay using various explanatory variables such as runway distance, queue position, arrival and departure rates, and weather. Rebollo and Balakrishnam (2012) proposed random forest algorithm-based models for air traffic delay prediction.

Contemporarily, in addition to developing flight time prediction models, some researchers were interested in computing the probability of flight delays. For example, Mueller and Chatterji (2002) proposed computing the probability of departure and arrival delays using Poisson and normal distributions, respectively. Tu et al. (2008) suggested a prediction model using daily propagation effects and seasonal trends for forecasting flight departure delays using a spline smoothing-based nonparametric additive approach. Meanwhile, parametric mixture distribution was applied to model residual errors, which were utilized to compute the probability of a delay. Deshpande and Arıkan (2012) suggested forecasting the truncated total travel time using various predictor variables such as routes, carrier, origin and destination airports, congestion, and aircraft-specific variables. They assumed that travel time follows log-normal and log-Laplace distributions, and calculated on-time arrival probability under these distributions.

In the current study, prediction models with nonparametric additive techniques are applied to the short-term forecasting of flight arrival time, which is extended from the approaches by Tu et al. (2008). Flights arriving data at Denver International Airport in 2010 and 2011 from various U.S. cities are used to estimate and forecast the model. Various predictor variables related to airborne state, and departing and arriving airports are implemented. Linear regression and median regression are also employed as benchmark models. The predictability performance between models is evaluated using point-wise prediction criteria. Lastly, the residual errors are modeled using the skew t distribution, which is utilized to compute the probability of the arrival delay.

E-mail address: myungkim@sogang.ac.kr.

http://dx.doi.org/10.1016/j.jairtraman.2015.12.002
0969-6997/

Our research findings make two important contributions to the literature. First, they show that departure delay time is very important in providing substantial improvements in the prediction accuracy of flight arrival time. In our analysis frame, arrival delay forecasting proceeds from the point at which a flight takes off from a departing airport. Therefore, departure delay information is available in the prediction. Although the forecasting horizon is very short, the newly collected delay time information can be utilized to update the prediction outputs depending on the availability of real-time business intelligence. Eventually, improved prediction may lead to more efficient air traffic control at the arriving airport. Second, we found that the skew t distribution is statistically appropriate to model the fitted residuals. Existing distributions were shown to be invalid through goodness-of-fit test, or no rigorous statistical goodness-of-fit test was implemented. Therefore, accuracy of computing the probability of arrival delay will improve.

The remainder of this article is organized as follows. In Section 2, data and variables are explained. The forecasting models are suggested in Section 3, wherein the nonparametric additive models and their benchmark models are described. Section 4 reports the forecasting results of each model. The arrival time probability using the skew t distribution is computed in Section 5. Concluding remarks are given in Section 6.

2. Data and variables

U.S. air carriers whose customers represent at least one percent of total domestic scheduled-service passengers are supposed to report their airline on-time data every month to the U.S. Department of Transportation (DOT) and the Bureau of Transportation Statistics (BTS). The data cover all nonstop scheduled-service flights between areas within the United States. This study employs DOT data on domestic air flights arriving at Denver International Airport from more than 100 cities in the United States. Because our approach focuses on short-term forecasting, this analysis excludes international flight arrivals. From a list of the top ten airlines in the United States based on 2010 passenger numbers, the top seven air carriers were selected, comprising Delta, United, Southwest, American, US Airways, Trans World Airlines, and SkyWest. Complete historical flight data of seven air carriers for all of 2010 were implemented in the model estimation, whereas forecasting performance was evaluated using data for all of 2011. Cancelled and diverted cases were deleted from the data set. A total of 187,514 and 171,971 air flights arriving at Denver International Airport were applied for 2010 and 2011, respectively.

2.1. Response variable

According to the DOT, a flight is classified as delayed if it arrives at the departing or arriving gate 15 min later than its scheduled time. However, no globally standardized method exists to measure flight delay. Flight delay was modeled using numerous methods. For example, Idris et al. (2002) and Srivastava (2011) considered the taxi-out delay, which is the duration between pushback and takeoff. Mueller and Chatterji (2002) and Tu et al. (2008) applied the pushback delay that is measured using the difference between the scheduled departure time and the actual departure time. Xu et al. (2008) employed positive and negative delays using the difference between scheduled arrival time and actual arrival time in some phases. Deshpande and Arıkan (2012) applied truncated total travel time delay that is measured using the discrepancy between departure time and arrival time.

In our model, the arrival delay is considered. Arrival delay is actual arrival time minus scheduled arrival time. Thus, positive, negative, or zero values are available. A negative computed arrival delay implies an early arrival. The descriptive statistics for arrival delay for 2010 are summarized in Table 1, which shows that their distributions are heavily skewed to the right, similar to the results of previous studies (Mueller and Chatterji, 2002; Tu et al., 2008).

Some authors transformed the target response variable to reduce the heteroskedasticity problem. For example, Deshpande and Arıkan (2012) took a log-transformation to the truncated total travel time. We attempted to employ the log-transformation, but it was not applicable to the negative values of the response variable. Therefore, before the log-transformation, we transformed all the possible negative values into positive ones by adding 150. Note that the minimum value of arrival delay is -81. Thus, 150 is big enough to switch the negative value cases into positive ones. That is, the original arrival delay is notated as N_i, whereas the forecasting will proceed using $y_i = \ln(N_i + 150)$.

2.2. Predictor variables

According to the BTS regarding all air carriers arriving at and departing from Denver International Airport in 2010, the percentage of flight delays reached approximately 16.4% of total flights. The detailed airline on-time statistics and delays are summarized on the BTS website (see http://www.transtats.bts.gov/ot_delay/ot_delaycause1.asp), which reports statistics for flight delay causes: air carrier delay (3.48%), aircraft arriving late (6.61%), security delay (0.04%), national aviation system delay (4.38%), extreme weather (0.42%), and cancelled and diverted (1.43%).

In this study, the causes of flight delay were reorganized into three groups based on the sources of arrival delays or early arrivals. These three sources are departing airport, airborne state, and arriving airport, which are summarized in Table 2.

Arrival delays are often caused by departure delays at the departing airport. Many factors influence departure time. For example, the congestion period and a relatively busy airport are seasonal and regional factors that affect airport capacity. Mayer and Sinai (2003) pointed out that air delays are influenced by airline hub size and airport concentration. Deshpande and Arıkan (2012) also considered how a hub airport affects flight delays. Rebollo and Balakrishnam (2012) claimed that time of day is the most important factor for departure delays. On the other hand, Papakostas et al. (2010) pointed out that the flight delay depends on the availability of the resources at each airport. Weather conditions tend to disturb scheduled flight departures and arrivals (Allan et al., 2001; Xu et al., 2008). The airline itself is also a significant factor in departure delays, implying that some airline departures are delayed more frequently than others given the frequent occurrence of late aircraft delays, baggage loading, maintenance, cleaning, and so on (Srivastava, 2011).

All of these factors stemming from the departing airport are reflected in a delayed departure time. Therefore, departure delay time as provided by the departing airport is utilized as a predictor variable. Departure delay time indicates the difference between the actual and scheduled departure time, and is measured in minutes. As with arrival delay times, departure delay times can be negative, indicating an earlier departure than was scheduled. According to panel (a) in Fig. 1, departure delay times and log-transformed arrival delay times seem to have a strong nonlinear positive association. Note that this plot was generated from 2010 data.

In an airborne state, scheduled airborne time (measured in minutes) is an important predictor variable. According to Nikoleris et al. (2012), most flights are able to absorb assigned delays resulting from demand capacity imbalances by reducing their speed. Likewise, departure delayed flights may be able to shorten their delays by increasing their speed. If the scheduled airborne