Journal of Air Transport Management 35 (2014) 87–91

Contents lists available at ScienceDirect

Journal of Air Transport Management

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

Validating delay constructs: An application of confirmatory factor analysis

Tony Diana*

Federal Aviation Administration, 800 Independence Avenue S.W., Washington, DC 20591, USA

Keywords:
Delay
Airport capacity
Arrival and departure demand
Confirmatory factor analysis

A B S T R A C T

This paper proposes to use confirmatory factor analysis (CFA) to evaluate the relationship between six observed variables (arrival and departure counts, arrival and departure demand, taxi-out and airborne delays) and their underlying latent (unobserved) constructs (operations, demand, and delays) at six of the most delayed airports (EWR, JFK, LGA, MIA, ORD, and SFO) during the calendar years of 2006–2008. The CFA revealed a good fit between the six observed variables and the three factors that may explain on-time performance except in the case of JFK. The use of CFA can help analysts validate constructs when theory supports *a priori* predictions and relationships between observed and unobserved variables.

Published by Elsevier Ltd.

1. Introduction

In theory, delays represent the outcome of a trade-off between demand for arrivals and departures and available airport capacity. When an airport does not have enough capacity to satisfy demand, flights get delayed and sometimes cancelled. In this study, airport capacity is understood as the sum of an airport's arrival and departure rates. Delays usually increase to the point where congestion requires traffic management initiatives (TMI) such as ground delay programs or miles-in-trail in order to re-balance demand with capacity and to maintain a certain level of service (i.e. departures and arrivals within 15 min of airlines' published schedules[1]). In a context of constrained budgets and environmental scrutiny, airport operators do not have much time and resources to construct a new runway soon enough to improve on-time performance as demand grows. In fact, it takes more than a decade for an airport to open a new runway to traffic—often at a cost of over one billion dollars and lengthy litigations with surrounding communities opposed to airport expansion. Moreover, delays do not remain a local problem: They propagate throughout the National Airspace System (NAS) that constitutes a system of interdependent airports (Wu, 2010). The theoretical background that supports this article can be found in De Neufville and Odoni (2003), Janic (2009), Belobaba et al. (2009), and Horonjeff et al. (2010).

This paper proposes to use confirmatory factor analysis (CFA) to evaluate the relationship between six observed variables (i.e. arrivals and departures, arrival and departure demand, taxi-out and airborne delays) and their underlying latent (unobserved) constructs (i.e. operations, demand, and delays) at six of the most delayed airports during the 2006 to 2008 time period regardless of each airport's specificities (i.e., number of runways, percentage of operations in instrument meteorological conditions, among others). Table 1 of the appendix provides the details on on-time performance by sampled airport and calendar year. CFA allows analysts to determine whether the hypothesized structure provides a good fit to the data. Is there a relationship between the six manifest and the three latent factors which may explain poor on-time performance at the selected airports? The use of CFA can help aviation analysts validate constructs and eventually predict on-time performance.

Although CFA is popular in the fields of psychology and social work, it has not been widely utilized in research studies on aviation delays and airport capacity. Liedtka (2002) used CFA to investigate the information content of nonfinancial performance measures in the airline industry. Park (2007) evaluated the effects of airline service quality on airline image and passengers' future behavioral intentions. He examined passengers' perception of eleven factors that may influence their buying behavior and concluded that passenger perceptions are significantly different across airlines, seat classes, and usage frequencies. Babbar and Koufteros (2008) used a confirmatory approach to determine how much personal touch

This article does not reflect the official opinion of the Federal Aviation Administration.

* Tel.: +1 202 385 7311.
E-mail address: Tony.Diana@faa.gov.

[1] Under Title 14, Part 234 of the Code of Federal Regulations (14 CFR 234), a delay is defined as any gate departure or arrival time greater than 15 min in comparison with the airline's published schedule.

0969-6997/$ – see front matter Published by Elsevier Ltd.
http://dx.doi.org/10.1016/j.jairtraman.2013.11.014

Table 1
Variables and data sources.

Variable	Definition	Data sources
Total volume of arrivals and departures	The respective counts of individual incoming and outgoing flights	TFMS, ASPM
Arrival demand	The number of aircraft that have taken off but not yet landed at the destination airport	ASPM
Departure demand	The number of aircraft that have left the gate but not yet taken off	ASPM
Taxi-out delay	The difference between taxi-out time (from gate-out to wheels-off time) and an unimpeded taxi-out time.	ARINC's Out-On-Off-In data, ASPM, ASQP
Airborne delay	The difference between airborne time and the flight plan's estimated time enroute	ASPM

Note. TFMS, Traffic Flow Management System; ASPM, Aviation System Performance Metrics; ASQP, Airline Service Quality Performance.

Table 2
The variables at the six sampled airports (CY 2006–2008).

Variables	EWR			JFK			LGA			MIA			ORD			SFO		
	2006	2007	2008	2006	2007	2008	2006	2007	2008	2006	2007	2008	2006	2007	2008	2006	2007	2008
Average daily departures	609	594	594	524	610	605	551	538	521	516	516	493	1309	1269	1203	492	508	519
Average daily arrivals	572	575	571	502	598	591	551	547	528	443	443	433	1285	1275	1207	434	460	484
Average daily departure demand	984	952	970	894	1116	964	795	838	808	531	532	524	1557	1505	1407	512	546	553
Average daily arrival demand	1118	1160	1100	650	911	888	907	985	936	534	530	510	2055	1951	1861	629	665	749
Average minutes of taxi-out delay	15.4	15.2	15.6	17.1	18.9	14.3	13.0	15.0	14.7	3.4	3.5	3.4	7.8	7.6	7.0	4.4	5.3	4.5
Average minutes of airborne delay	6.2	5.5	4.8	6.0	7.2	6.3	6.0	6.9	7.3	2.2	1.9	2.9	3.6	3.8	3.9	3.1	3.4	3.6

displayed by contact employees is likely to have an impact on passenger satisfaction.

The six sampled airports include Newark Liberty (EWR), New York John F. Kennedy (JFK), New York LaGuardia (LGA), Chicago O'Hare (ORD), Miami International (MIA), and San Francisco International (SFO). Only LGA does not serve as a key international gateway among the sampled airports. The six observed variables were measured at a time when poor on-time performance led the FAA to intervene through demand management initiatives. In 2008, flights were capped at EWR and JFK during peak hours[2] (LGA already had limits on flights). From 2006 to 2008, the number of hourly arrivals at ORD could not exceed 88 from 07:00 to 19:59 local time. Moreover, the variables under consideration were observed prior to three events that have changed the U.S. aviation landscape: (1) the recession that hit the U.S. economy in 2008, (2) a decline in passenger demand that led to airlines' schedule reductions and (3) airline consolidations.

The next section defines the variables and their data sources. After briefly outlining the differences between exploratory and confirmatory factor analysis, the discussion will proceed with a description of the CFA model and then an explanation of its outputs.

2. The data

The CFA model includes the following variables aggregated at the monthly level for the calendar years 2006, 2007 and 2008. The data were collected from the Aviation System Performance Metrics (ASPM) data warehouse.[3] The variables, definitions and data sources are specified in Table 1.

Table 2 provides quantitative data about the six variables for the three years under consideration. The three New York airports and ORD show a strong imbalance between demand and recorded operations that is likely to result in poor on-time performance.

Although more variables such as taxi-in and block delays were initially introduced into the model, the number was reduced to the six identified ones in this paper on the basis of improvement in the Parsimonious Goodness-of-Fit Index (PGFI) and other goodness-of-fit statistics specified later in Table 3. Moreover, these six variables play a significant role in the theory of delay and delay modeling. Their interactions often explain airport delays and congestion. As demand increases, departing aircraft are likely to experience delays because air traffic control can only process so many planes per hour due to (1) the choice of runway configuration dictated by wind direction, ceiling, and visibility, (2) separation requirements that limit throughput (i.e. the volume of operations in periods of sustained demand), and (3) enroute congestion.

The next section focuses on the CFA methodology and its use to test whether there is a relationship between the observed variables and the latent factors as a predictor of poor on-time performance.

3. Methodology

3.1. Exploratory v. confirmatory factor analysis

Exploratory factor analysis (EFA) differs from confirmatory factor analysis (CFA) in that the former is mainly designed to explore the underlying factor structure of a set of observed variables without any preconceived model or structure of the outcome (see Child, 1990). EFA enables the determination of underlying constructs for a group of measured variables. EFA does not postulate any relationship pattern *a priori*, nor does it pertain to test hypotheses related to theoretical models.

On the other hand, CFA makes it possible to test whether a relationship between observed variables and underlying latent construct exists. CFA is grounded in theories and it requires the specification of an *a priori* model, the determination of a number of factors, as well as the identification of which variable loads on each

[2] At JFK, the total operations target was 80 operations per hour, except for the 15:00 through 19:59, when it was 81 total operations. The 30-min maximum was 44 operations and the 15-min maximum was 24 operations.

[3] The ASPM data warehouse is accessible at https://aspm.faa.gov.

Download English Version:

https://daneshyari.com/en/article/1030875

Download Persian Version:

https://daneshyari.com/article/1030875

Daneshyari.com