Winter 2015

Identification of Air Traffic Management Principles Influential in the Development of an Airport Arrival Delay Prediction Model

David C. Ison
Embry-Riddle Aeronautical University - Worldwide, isond46@erau.edu

Linda Weiland
Embry-Riddle Aeronautical University - Worldwide, weila8f3@erau.edu

Ian McAndrew
Embry-Riddle Aeronautical University - Worldwide, mcand4f1@erau.edu

Kat Moran
Embry-Riddle Aeronautical University - Worldwide, morank@erau.edu

Follow this and additional works at: https://commons.erau.edu/jaaer

Introduction

Flight delays result in caustic disturbances to the aviation industry and its stakeholders. Airlines incur increased costs and the disruption of flight schedules. In 2011, there were over 103 million minutes of delay at a cost of $7.7 billion to airlines. It has been estimated that each minute of delay costs each delayed aircraft within an airline fleet $75.27 (Airlines.org, 2003; Bureau of Transportation Statistics, 2013). Airlines also consumed an extra 740 million gallons of jet fuel due to delays. Passengers may miss connections, important meetings, or simply be frustrated with the uncertainty that accompanies such disturbances. Costs to passengers have been estimated to be in excess of $20 billion. Airports also suffer: Reid (as cited in NATS, 2013) noted, "without effective ATM [Air Traffic Management], an airports growth strategy and business model is at significant risk of not being realized." Of course delays are not beneficial to the environment either and, as a result of a year's worth of flight delays, an extra 7 million metric tons of CO_2 were emitted by aircraft (Joint Economic Committee, 2013). Large-scale political and economic anxieties have arisen, for example, concerns have been voiced in the U.K. that slot restrictions, capacity saturation, and delays at London Heathrow may be detrimental to economic growth of the country (Airport International News, 2008). Five primary airports in the New England region of the U.S. (Newark, Philadelphia, Boston, Washington National, and New York La Guardia) are notorious for delays with an average of 27% of flights being delayed each day creating air transport gridlock that detrimentally affects the entire air transportation network of the U.S. (CNN, 2013; Diana, 2011). Troubled airports in Europe include London Heathrow, Paris Charles De Gaulle, Frankfurt, Amsterdam, and Madrid (Morisset & Odoni, 2011). Unfortunately, air traffic is expected to continue to grow over the next several decades further exacerbating existing, inadequate and highly tasked facilities (Abdel-Aty, Lee, Bai, Li, &

Michalak, 2007). Just from 2011 to 2012, the average worldwide traffic increased 5% with the fastest growth in Asia (9%) and the Middle East (20%) (Amadeus Air Traffic Travel Intelligence, 2013). Moreover, the number of aircraft expected to take the skies within the next 10 to 20 years is expected to steadily rise (Airbus, 2012; Coy, 2006).

As a result of all of these issues related to flight delays, more pressure has been placed upon air traffic control to mitigate disruptions while at the same time public pressure on government entities, e.g. the Federal Aviation Administration and airport authorities, has increased calling for more solutions to ease the problem of delays. In the past, slot controls were used at busier airports yet this apparently has not eased the problem in light of recent statistics. Both the U.S. and Europe have pushed to assuage delays through aggressive air traffic management (ATM) overhauls, referred to as NextGen and SESAR (Single European Sky ATM Research), respectively. These new paradigms in ATM rely heavily on precise decision tools, in particular, accurate delay prediction (FAA, 2011). The planned 4-D[1] traffic control and queuing will require timely information about current and forecasted delays. Effective delay prediction has been identified as particularly critical during the transition from current ATM operations to NextGen/SESAR as there is likely to be a mix of 4-D capable and non-compliant aircraft (Booker, 2009).

Additional stimulus to seek improved delay prediction stems from observations by Xu, Sherry, and Laskey, who noted that exigent research does not adequately address the needs of future ATM structures. Existing prediction models do not sufficiently address the ATM principles that may be able to assist in delay relief. In addition, considering that 95% of delays in the U.S. occur in the airport terminal area rather than while enroute, it is particularly critical to

---

[1] 4-D refers to adding time as an aircraft sequencing tool, i.e. aircraft may be required to navigation to waypoint at a specific time as part of air traffic separation procedures (Xu, Sherry, & Laskey, 2008).

examine what adjacent air traffic control enroute sectors, approach controls, and control towers can do to assist in coping with delays. As such, this study began to investigate potential ATM principles that could assist in the prediction of airport arrival delays for use in collaborative decision-making (CDM) tools that are principal components of NextGen and SESAR 4-D navigation management (Xu, Sherry, & Laskey, 2008).

Current Delay Model Research

A variety of research has been conducted on the causes and prediction of air traffic delays. This study sought the most relevant data on airport arrival delays, although arrival and departure delays often influence one another. As Brooker noted, there is a constant struggle between capacity and delay – as movement rates decrease, delays increase (Abdel-Aty et al., 2007; Brooker, 2009; Diana, 2011; Nayak, & Zhang, 2011; Santos & Robin, 2011; Xu, Sheery, & Laskey, 2008). The goal being to achieve and maintain maximum sustainable throughput for a particular airport (Brooker, 2009). Brooker (2009) utilized queuing theory to develop a modest prediction formula two classes of user priority. However, the prediction model proposed by Brooker (2009) was rather simple and used linear analysis that other researchers have indicated to be inadequate for the highly complex airport movement organism.

Diana (2011) used spatial analysis to formulate a delay prediction model. Factors that were considered included weather, runway configuration, wind angle, taxi-in time, taxi-out time, arrival demand, arrivals and departures, total minutes of departure delays, and total minutes of arrival delays. Spatial autocorrelations among variables were analyzed with Geary's c and Moran's I. A spatial error model was then developed using regression techniques. The resultant regression model determined the influence of closely spaced airports on one another. Not surprisingly there was a close relationship between arrival demands at both New York airports

(LGA and JFK) and the minutes of delay at Newark airport (EWR). The findings of this study are important, however, in determining the best ATM practices to accommodate all local airports collectively and could be used as part of a larger prediction-modeling schema (Diana, 2011).

Taking a two-step approach to model development, Abdel-Aty, et al. (2007) first identified periods of common delays and then investigated the correlation of delay frequencies. The advantage of this formulation was that it accommodated seasonal, time of day, day of the week, and specific date delay fluctuations and commonalities. Multinomial and binary logistic regression, as well as ANOVA, were utilized in the model. Higher levels of delays were detected on Thursday and Friday, as well as in summer months. The length of the flight in miles was found to be a factor, but only for those flying 750-1000 miles (Abdel-Aty et al., 2007). Again whilst this model is helpful it does not completely describe or predict the necessary aspects required in high volume, advanced ATM terminal environments (Xu, Sherry, & Laskey, 2008).

Realizing that simplistic models were inadequate for reliably predicting flight delays, Xu, Sherry, & Laskey (2008) utilized a multivariate adaptive regression splines (MARS) approach to integrate a wider number of variables. This model included more weather related items, in particular convective activity which has significant effects on aircraft movements. The National Convective Weather Detection (NCWD) database was used to improve prediction power. Other key variables that were included were the ratio of operational demand versus airport capacity, enroute weather (using the Weather-Impacted Traffic Index [WITI]), time of day, aircraft swap rate, and carrier delays. This study attempted to validate the model using historical data and was accurate within approximately 5 minutes. Yet the authors did not attempt to use the model to make actual predictions based upon current conditions. Any delay between the issuance of

included variables and the calculation of delay prediction could be problematic (Mueller &

Chatterji, 2012; Xu, Sherry, & Laskey, 2008).

Morisett and Odoni (2011) studied 64 high volume airports in the U.S. and Europe to

determine if they had different delay characteristics. Significant disparities between the two

continents existed. European airports had lower airport arrival rates due to the commitment to

operate with IFR (poor weather) separation even in VFR (good weather) conditions. Although

U.S. airports typically had much higher AARs, there was more variation in delay levels in the

U.S. than in Europe. European slot control, albeit tedious, appears to assist in the mitigation of

delays, particularly vis-a-vie the less intrusive ATM restrictions in the U.S. This study also

identified the need to consider runway configurations as U.S. airports tend to have more

complicated runway arrangements (average of 4.12 runways per airport) than European airports

(average 2.47 runways per airport) (Morisett and Odoni, 2011). Other key findings included that

the time of day was a critical aspect of delay prediction as well as the lack of consistency in

delays in the U.S. relative to Europe due to the differences in flow control procedures.

Another key study identified the importance of considering severe, namely convective,

weather in reliable delay forecasting. Sridhar and Chen determined that 70% of all delays were

due to weather of which 60% were a result of convective (thunderstorm) activity. Instead of

utilizing the generic WITI, these authors modified it into a dynamic model referred to as the

predicted-WITI and was developed using autoregressive models with exogenous inputs. The

advantage of this index is that it is updated more frequently and has a forward-looking function

rather than a current or retrospective view (Sridhar & Chen, 2009).

While all of these studies have provided significant insight into what causes air traffic

delays and some reasonable ways to predict them, several critical considerations are missing.

One is the considerations of air traffic management principles that can possibly positively (or negatively) influence delays. Moreover, new aspects of NextGen and SESAR may need to be considered in prediction models have been generally ignored. Another concern is the lack of a coordinated model that takes into account previous prediction research combined with the input of air traffic management experts. Careful consideration is required to strike a balance between including a sufficient number of viable variables into the model without over-saturating a delay forecast with too many variables that would thus create unwanted, inflated variance (Abdel-Aty, 2007; Diana, 2011; Xu, Sherry, & Laskey, 2008). The goal of this study was to initiate the investigation of an all-encompassing delay prediction model with special consideration for new-era traffic management systems.

Method

The first step of this study was to demonstrate a survey development and editing procedure through an exhaustive literature review of recent, exigent literature on air traffic delay prediction. Once the instrument was refined into a draft form, a qualitative analysis of the validity of the survey was conducted using an inquiry posed to a panel of non-participant experts. Following the editing and revision of the survey, it was distributed to a purposive sample of air traffic management experts composed of controller supervisors, air traffic control faculty, and air traffic management stakeholders.

Survey Development

The systematic instrument development process presented by Dillman provided a model for the development of an instrument that included the recommendation for the use of a panel of experts to evaluate the prototype version. The checklist for the development of a survey

instrument authored by Creswell (2003) was utilized to guide the production process (Creswell, 2003; Dillman, 2007).

Preparation, Piloting, and Revision

The prototype version was evaluated through the enlistment of a panel of non-participant experts. Feedback was incorporated into the final version that was distributed for completion (Estes, 2008).

It is important to note that this study sought to serve as a foundational pilot for future study and development of a delay prediction model therefore there was no intent to seek a large sample (Creswell, 2003). Rather than seeking numerous respondents, nonrandom, purposive sampling was utilized in the selection of the participant experts (Patton, 2002). As Gay and Airasian (2000) noted, purposive sampling is highly appropriate in qualitative research. This type of sampling was deemed the most appropriate for the goals of this study. The survey was also made open ended thus lending itself to yield more rich, qualitative data.

It was noted that the list of potential panel members should be identified that consisted of individuals with critical knowledge and/or skills necessary for adequate evaluation of the survey instrument (Gisev, Bell, O'Reilly, Rosen, & Chen, 2010). The primary required skill was significant experience in air traffic management. The sample membership included air traffic controllers, air traffic control faculty, and air traffic management organization stakeholders. Potential panel members were identified via the FAA Air Traffic Control College Training Initiative database that was then mined for faculty (FAA, 2012). Additional air traffic controllers and air traffic management stakeholders were identified with the assistance of snowballing. Potential respondents were sent an email invitation notice with a link to the survey administered through SurveyMonkey.

Results

A total of ten responses were collected out of a total of twenty five invitations resulting in a 40% response rate (albeit arguably moot for the pilot nature of this study). When asked to rank the top five reasons for airport arrival delays, all but one respondent (90%) stated weather was the number one cause. The remaining answer was "competition for certain time slots." See Table 1 for a summary of the ranked causes of arrival delays. When asked for other reasons for delays, respondents added that staffing was an issue, convective weather, gate availability, taxi delays, wind direction, wind velocity, too much demand on limited infrastructure, and need for expanded airports and more runways.

When asked how air traffic management may influence arrival delays, respondents stated the following:

- Need procedures for dealing with circumnavigating weather and avoiding congestion points

- Introduce congestion slots

- Reduce ATC separation

- Relax approach, land and hold short (LAHSO), and landing separation minima

- Better route management and controller training on airspace

- Seasonal/holiday restrictions

- Need to better manage airport construction projects to minimize effects on delays

- Limit mix of aircraft to mitigate delays due to differences in speed/spacing

- Coordinate gate assignments with airlines, air traffic control, and airport to mitigate taxi delays

When asked to offer additional comments, the following were offered:

- NextGen will do nothing or little to reduce delays. Focus on airport capacity. The best way to increase capacity is to add runways.

- Enroute and approach spacing should match airport runway capacity.

- Runway layout should be optimized for taxiing aircraft.

Table 1

Respondent ranking of top five causes of airport arrival delays

#1	#2	#3	#4	#5
Weather (9)	Terminal cong. (6)	Enroute cong. (3)	Enroute cong. (3)	Taxi delays (2)
Slot compete	Mix of A/C	Season (2)	Time of day (2)	Lack of runways (2)
	Time of day	Weather (2)	Lack runways (2)	A/C positioning (2)
	Lack runways	Lack runways (2)	Time of day (2)	Controller staffing
	Construction	A/C problem	Route flown	Navigation problem
				Airspace cong.

Note: cong = congestion; A/C = aircraft

Discussion

It was not surprising that there was tremendous consensus about the influence of weather on airport arrival delays. While this revelation is not novel, it does point to the need to accurately model what aspects of weather most influence delay levels and, if predictable, must be included in the forthcoming forecast model. Of course, some factors have already been identified, such as visual versus instrument conditions, wind, and the influence of such on airport arrival rates however, further investigation is necessary on how to best predict and model the influence of distinct weather phenomenon at specific airports and in explicit terminal environments. As can be concluded from exigent literature as well as the results of this inquiry, each airport has unique factors that influence delays in and around the facility that cannot be detailed by a generic delay-forecasting model. Taking this notion a step further, it is likely that each airport runway configuration will require specific weighting and further complexity will be required when factoring universal and indigenous weather conditions. Moreover, the distinction between convective and non-convective weather must be made as the former has a greater level of influence on delays.

Time of day issues, terminal congestion, and lack of runways are clearly related to one another. The new model will need to address how these correlate to one another to build an accurate, live forecast that could be usable by air traffic management as well as by airport and air carrier stakeholders. Enroute congestion has been mostly ignored, perhaps peripherally considered through the integration of WITI data, however delay prediction would benefit from modeling for in-trail spacing and other restrictions.

Another key element identified in both the literature and from the survey results is the importance both airport arrival rates (AARs) and enroute congestion can have on arrival delays.

Undoubtedly, changes in AARs coupled with high levels of enroute traffic indicate trouble in the near term. Any reliable arrival delay forecast tool will need to compensate for these dynamic factors.

Further complicating delay prediction are aircraft route and taxi conditions. Aircraft arriving from certain directions during certain runway configurations and times of day may incur different levels of delay. If these patterns can be identified, they can create a more accurate delay profile. The same is true about taxi conditions – taxi-in and taxi-out delays – that can clearly influence the ability to effectively move aircraft around the airport. It may be necessary to break apart on-ground and in-air delay models to better identify and forecast specific aspects of deferment.

Conclusions

In order for NextGen, SESAR, and other forthcoming improvements to air traffic management to succeed, high quality, real-time delay forecast data will be needed to insure the optimum efficiency of such networks. Current forecast models are either too generic or insufficiently condense the complexity of air traffic flows and delays. Future delay prediction requires a careful balance of inclusion and exclusion of variables to insure stability in variability and reliability. It is apparent from the literature that consideration beyond weather and infrastructure limitations is necessary, thus this study sought to identify potential air traffic management principle based variables that may be of interest for inclusion in forecasting models. By combining the findings of this study with that found within available literature, a more detailed study can be designed to further investigate the production of an airport arrival delay prediction model. Moreover, this study identified the need for the customization of delay models for individual airports and terminal environments. Lastly, this study identified potential

weaknesses in current delay prediction as well as possible areas and procedures to be targeted by

air traffic management stakeholders to mitigate the causes of delays rather than simply predict

them.

References

Abdel-Aty, M., Lee, C., Bai, Y., Li, X., & Michalak, M. (2007). Detecting periodic patterns of arrival delay. *Journal of Air Transport Management, 13*, 355-361. http://dx.doi.org/10.1016/j.jairtraman.2007.06.002

Airbus (2012). Navigating the future: Global market forecast 2012-2031. Retrieved from http://www.airbus.com/company/market/forecast/

Airlines.org. (2013). Annual and per minute cost of delays to U.S. airlines. Retrieved from http://www.airlines.org/data/per-minute-cost-of-delays-to-u-s-airlines/

Airport International News (2008). *BA chief gives Heathrow Airport warning.* Retrieved from http://www.airport-int.com/news/ba-chief-gives-heathrow-airport-warning.html

Amadeus Air Traffic Travel Intelligence. (2013). *300 world 'super routes' attract 20% of all travel.* Retrieved from http://www.4hoteliers.com/news/story/11300

Brooker, P. (2009). Simple models for airport delays during transition to a trajectory-based air traffic system. *Journal of Navigation, 62*(4), 555-570. http://dx.doi.org/10.1017/S0373463309990105

Bureau of Transportation Statistics. (2013). Ranking of major airport on-time performance in January 2013. Retrieved from http://www.rita.dot.gov/bts/subject_areas /airline_information/airline_ontime_tables/2013_01/table_03

CNN. (2013). Worst U.S. airports for flight delays. Retrieved from http://www.money.cnn.com/gallery/pf/2013/05/02/flight-delays/index.html

Coy, S. (2006). A global model for estimating the block time of commercial passenger aircraft. *Journal of Air Transport Management, 12*(6), 300-305. http://dx.doi.org/10.1016/j.jairtraman.2006.07.005

Creswell, J. W. (2003). *Research design: Qualitative, quantitative, and mixed methods approaches* (2nd ed.). Thousand Oaks, CA: Sage Publications, Inc.

Deason, K., & Jefferson, T. (2010). A systems approach to improving fleet policy compliance within the US Federal Government. *Energy Policy, 38*(6), 2865-2874. http://dx.doi.org/10.1016/j.enpol.2010.01.019

Diana, T. (2011). Predicting arrival delays: An application of spatial analysis. *Journal of Aircraft, 48*(2), 462-467. http://dx.doi.org/10.2514/1.C031050

Dillman, D. A. (2007). *Mail and internet surveys: The tailored design method* (2nd ed.). Hoboken, NJ: John Wiley and Sons, Inc.

Estes, T. S. (2008). Assessing collaborative management in asthma: A pilot study. *Journal of Theory Construction & Testing, 12*(2) (2008), 63.

FAA. (2011). *U.S./Europe comparison of ATM-related operationalperformance.* Retrieved from http://www.faa.gov/air_traffic/publications/media/us_eu_comparison_2010.pdf

FAA (2012). *A plan for the future: 10-year strategy for the Air Traffic Control workforce 2012-2021*. Retrieved from http://www.faa.gov/air_traffic/publications/controller_staffing/media/CWP_2012.pdf

Gay, L. R., & Airasian, P. (2000). *Educational research: Competencies for analysis and application* (6th ed.). Upper Saddle River, NJ: Prentice-Hall, Inc.

Gisev, N., Bell, J., O'Reilly, C., Rosen, A., & Chen, T. (2010). An expert panel assessment of comprehensive medication reviews for patients of community mental health teams. *Social Psychiatry and Psychiatric Epidemiology, 45*(11), 1071-1079. http://dx.doi.org/10.1007/s00127-009-0148-8

Joint Economic Committee (2013). Flight delays cost passengers. Retrieved from

    http://www.jec.senate.gov/public/index.cfm?p=FlightDelaysCostPassengers

Morisset, T., & Odoni, A. (2011). Capacity, delay, and schedule reliability at major airports in

    Europe and the United States. *Transportation Research Record, 2214*(1), 85-93.

    http://dx.doi.org/10.3141/2214-11

Mueller, E., & Chatterji, G. (2012). Analysis of aircraft arrival and departure delay

    characteristics. *Proceedings of the Aircraft Technology Integration and Operations*

    Technical Forum, Los Angeles, CA.

NATS. (2013). Failure to develop air traffic management will have significant impact on airports

    in the Middle East. Retrieved from http://www.nats.aero/me/2013/05/09/failure-to

    -develop-air-traffic-management-will-have-significant-impact-on-airports-in-the-middle

    -east-says-nats/

Nayak, N., & Zhang, Y. (2011). Estimation and comparison of impact of single airport delay on

    National Airspace System with multivariate simultaneous models. *Transportation*

    Research Record, 2206(1), 52-60. http://dx.doi.org/10.3141/2206-07

Patton, M. Q. (2002). *Qualitative evaluation and research methods* (3rd ed.). London: Sage.

Santos, G., & Robin, M. (2011). Determinants of delays at European airports. *Transportation*

    Research Part B, 44(3), 392-403. http://dx.doi.org/10.1016/j.trb.2009.10.007

Sridhar, B., & Chen, N. (2009). Short-term national airspace system delay prediction using

    weather impacted traffic index. *Journal of Guidance, Control, and Dynamics, 32*(2)

    (2009), 657-661. http://dx.doi.org/10.2514/1.38798

Xu, N., Sherry, L., & Laskey, K. (2008). Multifactor model for predicting delays at U.S. airports.

    Transportation Research Record, 2052(1), 62-71. http://dx.doi.org/10.3141/2052-08