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Measuring the impact of traffic flow management on interarrival duration: An application of autoregressive conditional duration☆

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ABSTRACT

The Federal Aviation Administration has several tools in its arsenal to manage traffic flows. However, it is very difficult to assess with certainty the impact of traffic flow management procedures such as Time-Based Flow Management (TBFM) or Traffic Management Initiatives (TMI) on airport performance because operational data are not readily available to analysts. This study uses the case of Fort Lauderdale–Hollywood International Airport (FLL) where traffic flow management procedures have been implemented to manage a reduction of airport capacity due to runway constructions. Based on an Autoregressive Conditional Duration (ACD) model, the analysis shows that the use of traffic flow management procedures contributed to reducing the volatility of interarrival duration whether separation relies on time-metering (TBFM) or distance between aircraft (TMI). The lessons learned from this case study may have important implications for airports whose available capacity is severely constrained.

1. Introduction

The autoregressive conditional duration (ACD) model was originally developed by Engle and Russell (1998) to analyze time durations of traded stocks and to understand irregularly spaced transaction data. According to Washington et al. (2010:224), “duration models are concerned with the time elapsed until the occurrence of an event or the duration of an event.” ACD represents a particular class of dependent point processes since the conditional mean duration changes as a function of past durations over time.

In this article, ACD is applied to interarrival durations between aircraft at the final fix to test the hypothesis of whether traffic flow management procedures such as traffic management initiatives (TMI) and the increased use of time-based flow management (TBFM) have had a significant impact on interarrival durations when comparing the peak travel months of December 2009–January 2010 (Period 1) with December 2012–January 2013 (Period 2) at Fort Lauderdale–Hollywood International Airport (FLL). These time periods reflect pre- and post-runway construction. In fact, runway 9L | 27R has been closed from April 2012 through the time of this writing for widening and extension. It is expected to be operational in September 2014 and renamed as 10 R | 28 L. In May 2013, runway 13 | 31 was decommissioned. Despite runway closure and construction, FLL has been the busiest single runway airport in the U.S. with an average of 768 daily operations in Period 2 compared with 807 in Period1.[1] The runway configuration chart is provided in the Appendix for reference.

FLL provides an interesting case study with important operational and policy implications for the efficiency of the National Airspace System (NAS). Although airports are different based on runway configurations and traffic volume, it is important for aviation practitioners to understand how the experience of FLL with TBFM and TMI can be applied to other airports whose capacity can

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

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[1] Source: OPSNET (http://aspm.faa.gov).

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be severely constrained. At many facilities, the use of TBFM is usually sporadic and related operational data are not readily available. However, interviews of the airport operators and FLL tower management have revealed that TBFM has consistently helped the airport cope with sustained demand in the face of a drastic reduction in available airport capacity.[2] The airport lost 31.2% of its average daily capacity[3] between the two periods during the hours of 07:00 to 21:59 local. Modeling the pace of interarrival durations is of great significance to airline and airport operators: The former are interested in maintaining schedule adherence, predictable operations and reduced fuel burn. The latter are concerned with balancing demand with available airport capacity in order to minimize delays. Finally, as part of the Next Generation Air Transportation System (NextGen) portfolios of capabilities, TBFM is intended to improve the management of traffic flows from the en-route domain to the runway and to tactically adjust capacity and demand imbalances. NextGen represents a set of initiatives designed to transition the existing ground-based, air-traffic-controlled system into a satellite-based, air-traffic-managed airspace.

2. Traffic flow management tools

Air traffic controllers can regulate traffic flows either with TBFM or TMI. In the former case, air traffic controller separates aircraft using time-based metering. In the latter case, aircraft are separated mainly on the basis of distance such as miles-in-trail.

The Federal Aviation Administration (FAA) defines TBFM as "the technology and methods of balancing demand and capacity utilizing time".[4] TBFM is a technique designed to control aircraft flows by scheduling the time at which each plane should cross a predetermined meter reference element (MRE) such as an outer meter arc, a meter fix/arc, a final approach fix, and/or a runway threshold. A fix is essentially a geographical position that serves as point of reference in the course of a flight. TBFM has been primarily designed (1) to improve traffic flows into the Terminal Radar Approach Control (TRACON) facilities, (2) to minimize delays in the TRACON, (3) to smooth arrival throughput, (4) to help a facility manage its available capacity more effectively, and (5) to reduce a facility's dependence on miles in trail (MIT). The meter arc is a semicircle, equidistant from a meter fix, to help determine a meter time.

According to the FAA, "Traffic Management Initiatives (TMIs) are techniques used to manage demand with capacity in the NAS [National Airspace System]".[5] TMIs include procedures such ground delays, miles-in-trail, minutes-in-trail, altitude capping, airspace flow programs, and closed routes, among other tactics.

3. Methodology

3.1. Model assumptions

The time interval between arrivals represents the variable under investigation. ACD models are appropriate when durations between arrivals have the following characteristics:

- They are not fixed intervals
- They are likely to vary as a function of diurnal patterns such as peak hours
- They may be affected by stochastic events such as thunderstorms, and
- They are serially autocorrelated since interarrival durations at period $i-1$ may affect those at period i.

Interarrival durations also feature temporal dependences likely to vary with fleet mix and wake vortex separation requirements. The spacing of aircraft, like financial transactions in the Engle and Russell model, conveys some meaningful information about en-route and terminal area congestion, available airport capacity, preferences for tactical tools (TBFM and TMI) versus strategic tools (ground stops), and the use of arrival metering, among others.

3.2. Data samples and variables

According to unstructured interviews of FLL facility staff and subject-matter experts, traffic flow management procedures help cope with sustained demand as the available airport capacity was drastically curtailed. The intent of traffic flow management procedures is to smooth the delivery of aircraft to the runways. As the use of TBFM and/or TMI increases, interarrival durations is likely to feature less volatility in Period 2.

The number of sampled interarrival durations was 17,873 and 14,902 respectively in Period 1 and Period 2. A series of arrival-based duration data were used to model the time intervals between arrivals (interarrival durations) at the final fix. The model relies on the duration in minutes between two AZ messages from 07:00 to 21:59 (local). An AZ message determines the time of an aircraft arrival in the Traffic Flow Management System (TFMS). AZ messages for the selected flights originated from the Aviation System Performance Metrics (ASPM) data warehouse.[6] The messages sent by aircraft are used to construct the flight trajectory. Interarrival durations with less than 2 min and greater than 45 min were rejected. The minimum separation between two aircraft was set to 2 min based on wake vortex minimum time of separation.[7] A duration of 45 min between two aircraft would indicate that incoming traffic may have been impacted by ground stops at FLL.

[2] "Less Delay to Sun n' Fun with NextGen at Fort Lauderdale", NextGen Performance Snapshots, Federal Aviation Administration, June 2014, retrieved at http://www.faa.gov/nextgen/snapshots/stories/?slide=33.

[3] The available airport capacity is measured as the sum of airport arrival and departure rates. Source: ASPM (https://aspm.faa.gov).

[4] Retrieved from the Federal Aviation Administration, Air Traffic Organization Policy Notice, NJO7210.797, December 29, 2011, http://www.faa.gov/documentLibrary/media/Notice/N7210.797.pdf.

[5] See FAA Order JO 7210.3X of February 9, 2012 available at http://www.faa.gov/air_traffic/publications/atpubs/fac/1706.html.

[6] The website is http://aspm.faa.gov.

[7] Aircraft Wake Turbulence, Advisory Circular 90-23G, Federal Aviation Administration, February 10, 2014, retrieved at http://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_90-23G.pdf.

Table 1
The model estimates.

Time period	Estimates and t-value		
	ω	α	β
December 2009–January 2010	0.6222 (11.22)	0.1039 (20.22)	0.8476 (106.05)
December 2013–January 2014	1.3273 (12.88)	0.1616 (19.86)	0.6876 (41.00)

All coefficients significant at 95% confidence level (pr < 0.0001).

3.3. The weibull autoregressive conditional duration or WACD(1,1) model

The objective of ACD models is the modeling of irregularly spaced and autoregressive times between events, especially for high frequency data. The ACD models take into account the intensity of interarrival duration and express the conditional expectation of interarrival durations as an autoregressive relationship of past interarrival durations. According to Hautsch (2004: 80), "the basic idea of the ACD model is to (dynamically) parameterize the conditional duration mean rather than the intensity function itself." In this study, a Weibull ACD(r,s) model was selected:

$$\Psi_i = \omega + \sum_{j=1}^{r} \alpha_j x_{i-j} + \sum_{j=1}^{S} \beta_j \Psi_{i-j} \tag{1}$$

Ψ_i depends on r past durations and q past expected durations. ω represents a constant term, α_j the autoregressive coefficient for interarrival duration and β_j the autoregressive conditional estimate for interarrival duration. The conditional mean duration is a function of lagged durations and their conditional expectations. In the present case, r and s are equal to 1. The autoregressive form in Equation (1) describes periods of clustered interarrival durations such that shorter (longer) interarrival durations are followed by longer (shorter) interarrival durations. If x_i is the time duration between arrivals $i-1$ and i at the final fix, then the conditional expectations for times is

$$\Psi_i = \mathrm{E}[x_i | x_{i-1}, x_{i-2}, \dots, x_{i-n}] \tag{2}$$

The probability density function (pdf) for the scaled times is x_i/Ψ_i. The scaled times are assumed to be independent and identically distributed (i.i.d.) with $x_i = \Psi_i \varepsilon_i$. The random variables ε_i are i.i.d. with unit mean [$\mathrm{E}(\varepsilon_i) = 1$]. The residuals $\varepsilon_i = x_i/\Psi_i$ are called standardized durations.

We assume that ε_i has a Weibull distribution with a density characterized by the γ parameter. The Weibull distribution was selected because it is flexible: The Generalized Gamma and exponential distributions are special cases of the Weibull distribution that allows monotonically decreasing hazard functions.[8] The conditional density of the interarrival times is defined as follows

$$f(x_i|\Psi_i) = [(\gamma/x_i) y_i] \exp(-y_i) \text{ with } y_i = \left[x_i \Gamma\left(1+\gamma^{-1}\right) \big/ \Psi_i\right]^{\gamma} \tag{3}$$

The estimates and t-values for the WACD(1,1) models were derived using the MODEL procedure in SAS©.

[8] The hazard function of the Weibull distribution is expressed as $h(y|\alpha) = \alpha [-\Gamma(1+1/\alpha)]^{\alpha} y^{\alpha-1}$ with $y > 0$.

4. Findings and analysis

First, it is important to determine whether the selection of a Weibull distribution is appropriate in the present case. Based on Engle and Russell (1998), the test for the variance of the residual ε_i is computed as.

$$V = \frac{\sqrt{N(T)}}{\sqrt{8}} (\hat{\sigma} \varepsilon i - 1) \tag{4}$$

The dispersion values for Period 1 (869.13) and Period 2 (525.61) suggests that there is excess dispersion and that the distribution of ε_i is not likely to be exponential. This supports the choice of the Weibull distribution for ε_i. It is also significant to remark that variance of the residual almost declined by half in Period 2 compared with Period 1, which suggests less volatility in the interarrival duration and, therefore, a better allocation of the arriving aircraft to the runway. Since the Weibull shape parameter was respectively 1.2829 and 1.5074 in Period 1 and Period 2, we conclude that the conditional hazard function is monotonously increasing in the two periods. The persistence factor was higher in the Period 1 (0.9515) compared with Period 2 (0.8492), which implies more variability in interarrival durations in Period 1.

Second, Table 1 compares the constant, the estimates for the autoregressive coefficient for interarrival duration (α), the autoregressive conditional estimate for interarrival duration (β) and and t-values to test the hypothesis that the estimates equal zero, for the two periods under consideration.

The t-values indicate that all the estimates are significant at a 95% confidence level. The model estimates can be used to compute the expected adjusted interarrival duration: It was 12.83 min [0.6222/(1−0.1039−0.8476)] in Period 1 and 8.80 min in Period 2, a change of 4.03 min. The expected adjusted interarrival duration values confirm less volatility in Period 2 than in Period 1 and, therefore, less clustering of interarrival duration as intended by the use of traffic flow management initiative. It is also important to note that the decline in volatility occurred as the total volume of operations[9] decreased 7.2% in Period 2 (46,444) compared with Period 1 (50,070). However, while the number of air carrier operations increased 2.1%, air taxi and general aviation operations declined respectively by 33.2% and 20.7% in a Period 2 over Period 1 comparison. One of the main challenges at FLL is the significance of unscheduled general aviation traffic from the Caribbean region.

Moreover, the sum of α and β coefficients suggests the persistence of interarrival durations is weaker in Period 2 (0.8492) than in Period 1 (0.9515) and that the impact of new arrivals is dying off more quickly in Period 2. Arrivals are more spaced in time in Period 2, which results in a smoother delivery of aircraft to the runway as intended.

Third, Table 2 and Table 3 provide the autocorrelation (AC), partial autocorrelation (PAC) and Q-statistics with the probability to evaluate the model's goodness of fit. Autocorrelation measures the correlation between observations at different times. The autocorrelation coefficients organized as a function of separation in time provides the sample autocorrelation function that serves to

[9] OPSNET is the source of information (https://aspm.faa.gov).

Table 2
The autocorrelation, partial correlation and Q-Stat respectively for period 1.

Sample: 1 17873
Included observations: 17873

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.280	0.280	1396.7	0.000
		2	0.247	0.184	2491.2	0.000
		3	0.251	0.161	3621.0	0.000
		4	0.236	0.120	4615.0	0.000
		5	0.228	0.100	5543.9	0.000
		6	0.233	0.099	6517.3	0.000
		7	0.209	0.061	7298.3	0.000
		8	0.193	0.042	7961.6	0.000
		9	0.178	0.028	8529.7	0.000
		10	0.179	0.035	9102.4	0.000
		11	0.169	0.026	9613.6	0.000
		12	0.151	0.009	10021.	0.000
		13	0.135	-0.001	10348.	0.000
		14	0.132	0.007	10662.	0.000
		15	0.130	0.011	10962.	0.000
		16	0.108	-0.009	11172.	0.000
		17	0.097	-0.010	11342.	0.000
		18	0.077	-0.024	11449.	0.000
		19	0.078	-0.007	11558.	0.000
		20	0.084	0.008	11686.	0.000
		21	0.077	0.005	11793.	0.000
		22	0.061	-0.009	11859.	0.000
		23	0.050	-0.012	11904.	0.000
		24	0.045	-0.009	11940.	0.000
		25	0.052	0.007	11988.	0.000
		26	0.038	-0.007	12014.	0.000
		27	0.027	-0.014	12027.	0.000
		28	0.021	-0.011	12035.	0.000
		29	0.017	-0.009	12041.	0.000
		30	0.021	0.001	12048.	0.000
		31	0.017	-0.001	12054.	0.000
		32	0.028	0.017	12068.	0.000
		33	0.013	-0.002	12071.	0.000
		34	0.018	0.008	12076.	0.000
		35	0.020	0.008	12083.	0.000
		36	0.010	-0.003	12085.	0.000

Table 3
The autocorrelation, partial correlation and Q-Stat respectively for period 2.

Sample: 1 14902
Included observations: 14902

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.233	0.233	807.43	0.000
		2	0.206	0.160	1438.0	0.000
		3	0.168	0.098	1857.8	0.000
		4	0.150	0.074	2191.8	0.000
		5	0.134	0.057	2461.2	0.000
		6	0.095	0.016	2596.8	0.000
		7	0.082	0.014	2697.2	0.000
		8	0.049	-0.012	2733.4	0.000
		9	0.038	-0.008	2755.1	0.000
		10	0.048	0.016	2789.2	0.000
		11	0.024	-0.007	2797.8	0.000
		12	0.044	0.023	2826.1	0.000
		13	0.017	-0.008	2830.2	0.000
		14	0.032	0.016	2846.0	0.000
		15	0.042	0.025	2872.3	0.000
		16	0.037	0.014	2893.1	0.000
		17	0.037	0.012	2914.0	0.000
		18	0.026	-0.000	2924.2	0.000
		19	0.018	-0.008	2929.1	0.000
		20	0.021	0.002	2935.9	0.000
		21	0.025	0.008	2945.1	0.000
		22	0.020	0.002	2951.0	0.000
		23	0.024	0.011	2959.8	0.000
		24	0.015	-0.001	2963.4	0.000
		25	0.017	0.004	2967.6	0.000
		26	-0.007	-0.022	2968.3	0.000
		27	0.005	-0.001	2968.7	0.000
		28	-0.005	-0.010	2969.1	0.000
		29	-0.011	-0.012	2970.9	0.000
		30	-0.006	-0.002	2971.4	0.000
		31	-0.007	-0.001	2972.0	0.000
		32	-0.006	-0.001	2972.5	0.000
		33	-0.006	-0.001	2973.0	0.000
		34	-0.018	-0.014	2977.7	0.000
		35	-0.015	-0.008	2981.2	0.000
		36	-0.025	-0.016	2990.3	0.000

measure whether the series is random or not. For a random series, lagged values are not correlated and the autocorrelation coefficient is equal to zero. Partial autocorrelation plots are often used to determine the order of the autoregressive model. Partial autocorrelations measure the degree of association between various lags when the effects of other lags are removed. The Ljung–Box Q-statistic is used to test the hypothesis of whether any observed correlations among observations in a time series are random. One of the key assumptions for using an ACD model is that interarrival durations are serially autocorrelated.

If there were no serial correlation in the residuals, the autocorrelations and partial autocorrelations at all lags would be close to zero and the Q-statistics would be insignificant with large p-values. In Period 1 and 2, the Ljung–Box Q-statistics are significant at a 95% confidence level at all the lags. This indicates the presence of significant serial correlation in the residuals makes it appropriate to use the ACD model.

Illustration 1 provides a comparison of the conditional expectation of duration over 50 observations between the two time periods.

The graphic representation of the conditional expectation of duration shows less volatility in the interarrival duration in Period 2 than in Period 1 over a sample of 50 observations.

5. Conclusions and implications

Measuring the impact of traffic flow management techniques on airport performance and identifying the periods of traffic flow management use in surveillance data both represent a challenge for analysts. In the case of TBFM, for instance, there is a lack of readily-available data to track actual operational usage due to verbal instructions. Moreover, there are no publically-available data sources where information on usage and duration of TBFM and TMI operations is available.

To test the hypothesis that traffic flow management techniques have been used, analysts can resort to financial time series methods such as ACD to measure changes in traffic flow volatility. This article demonstrated that ACD is appropriate to evaluate the effect of air traffic flow management when the wait times between two aircraft crossing a point in space vary at random. The distribution of the

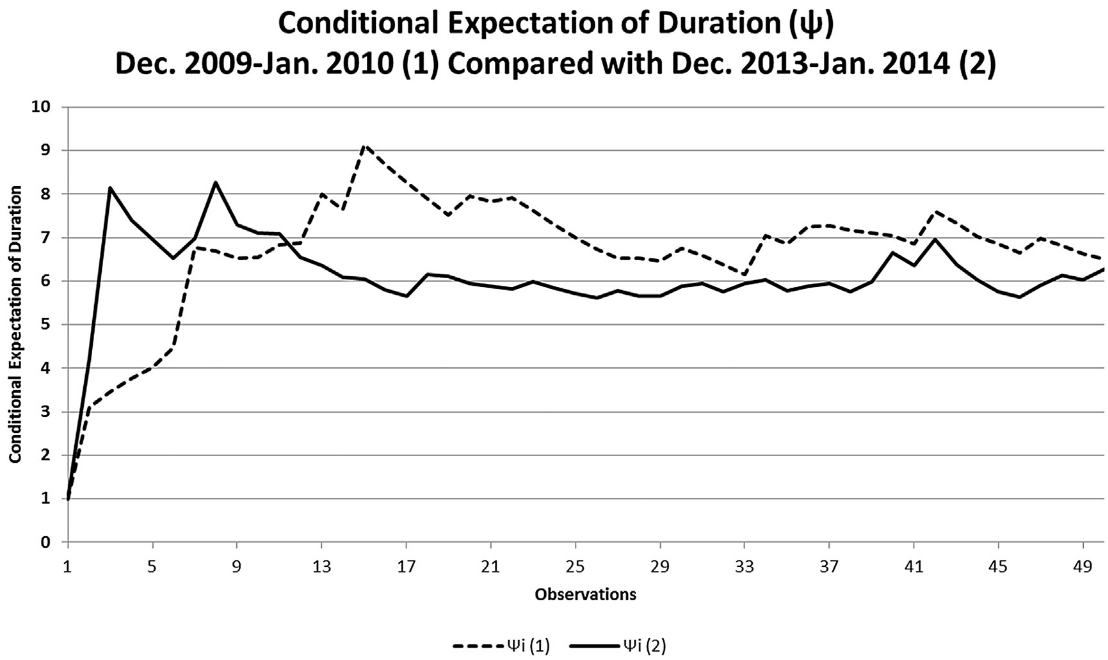


Illustration 1. Conditional expectation of duration.

interarrival durations is conditional on separation requirements based on wake vortex incidence, metering at a point in space and/or in-trail distance.

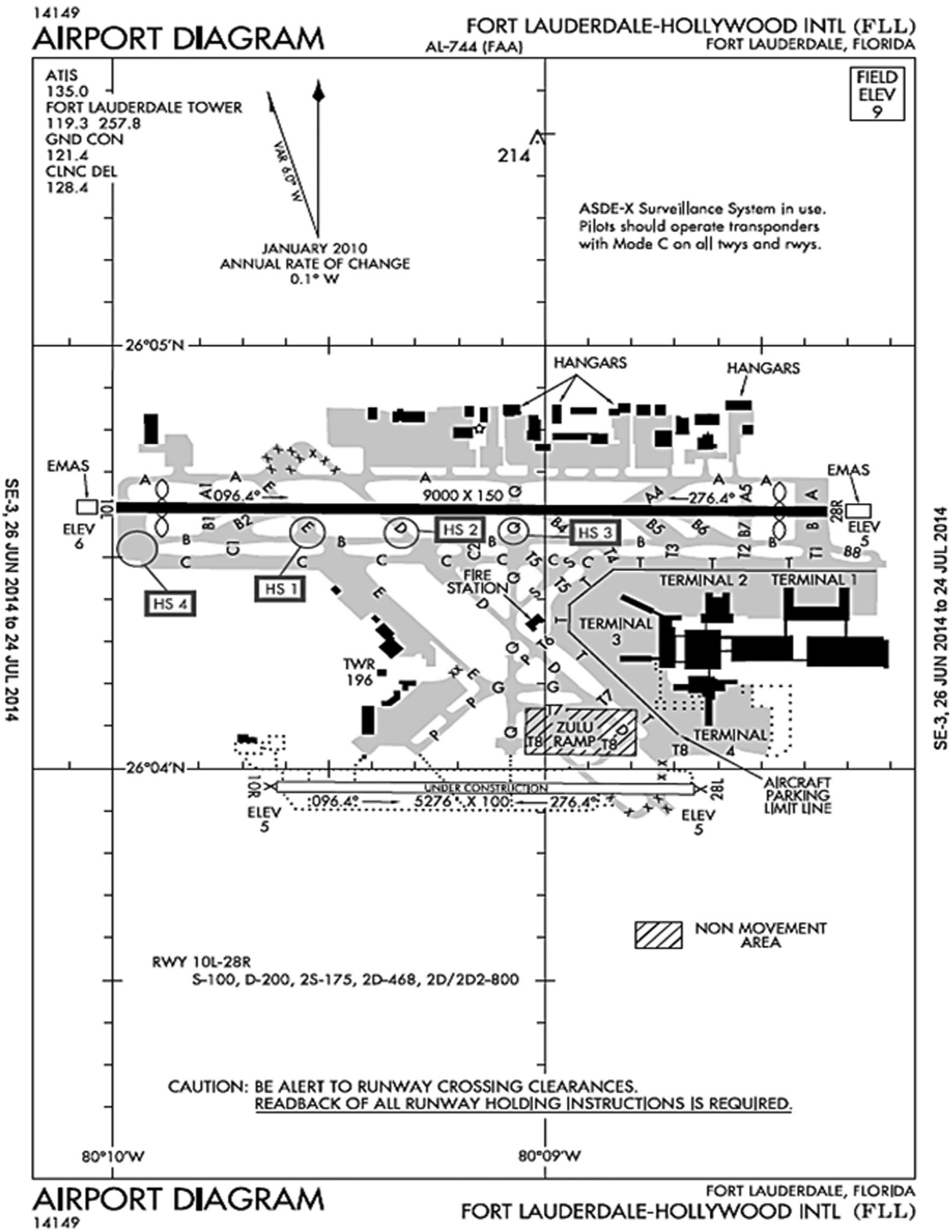
The Weibull ACD model revealed that the interarrival duration volatility decreased from December 2013–January 2014 (Period 2) compared with December 2009–January 2010 (Period 1) as air traffic flow management techniques were implemented to manage airport capacity. As the volatility of interarrival durations declined, airborne delays decreased from an average of 3.22 min in Period 1–2.55 min in Period2[10]. During the same time period, taxi-out times did not significantly increased: 16.70 min in Period 2 compared with 16.30 in Period1.[11]

The use of traffic flow management tools such as TBFM has significant implications on the efficiency of the NAS. First, although conditions vary from one airport to another, the case of FLL provides an example of how an airport can utilize TBFM to manage severely constrained capacity in the face of sustained demand. It takes decades to build a new runway, often as a result of surrounding airport community opposition. Therefore, TBFM allows a better utilization of existing resources within the enroute, terminal and airport domains. Second, TBFM represents a means of regulating the flow of traffic within the TRACON and allocating aircraft to the runway in a more predictable fashion, thus improving the transition from the enroute to the terminal environment. TBFM is more dynamic than TMI and can be extended to adjacent centers. Finally, the use of TBFM represents a key component in the success of NextGen, an effort to utilize satellite-based navigation to transition the existing radar-based air traffic control to a more air-traffic-managed system. It is, however, important to consider the use of TBFM as component that needs to be integrated into other capabilities such as optimized profile descent and integrated departures/arrivals capabilities.

Appendices

Fort Lauderdale–Hollywood Internal Airport Runway Configuration (Source: FAA).

[10] Source: ASPM data.
[11] Ibid.


14149
AIRPORT DIAGRAM
AL-744 (FAA)
FORT LAUDERDALE-HOLLYWOOD INTL (FLL)
FORT LAUDERDALE, FLORIDA
ATIS
135.0
FORT LAUDERDALE TOWER
119.3 257.8
GND CON
121.4
CLNC DEL
128.4
VAR 6.0° W
JANUARY 2010
ANNUAL RATE OF CHANGE
0.1° W
214
FIELD
ELEV
9
ASDE-X Surveillance System in use.
Pilots should operate transponders
with Mode C on all twys and rwys.
26°05′N
HANGARS
HANGARS
EMAS
EMAS
ELEV
6
ELEV
5
10L
28R
096.4°
9000 X 150
276.4°
HS 1
HS 2
HS 3
HS 4
FIRE
STATION
TERMINAL 1
TERMINAL 2
TERMINAL
3
TERMINAL
4
TWR
196
ZULU
RAMP
26°04′N
10R
28L
UNDER CONSTRUCTION
096.4°
5276 X 100
276.4°
ELEV
5
ELEV
5
AIRCRAFT
PARKING
LIMIT LINE
NON MOVEMENT
AREA
RWY 10L-28R
S-100, D-200, 2S-175, 2D-468, 2D/2D2-800
CAUTION: BE ALERT TO RUNWAY CROSSING CLEARANCES.
READBACK OF ALL RUNWAY HOLDING INSTRUCTIONS IS REQUIRED.
80°10′W
80°09′W
SE-3, 26 JUN 2014 to 24 JUL 2014
SE-3, 26 JUN 2014 to 24 JUL 2014
AIRPORT DIAGRAM
14149
FORT LAUDERDALE, FLORIDA
FORT LAUDERDALE-HOLLYWOOD INTL (FLL)

List of acronyms

Abbreviation	Term
ACD	Autoregressive Conditional Duration
ASPM	Aviation System Performance Metrics
FAA	Federal Aviation Administration
FLL	Fort Lauderdale–Hollywood International Airport
MIT	Miles in Trail
MRE	Meter Reference Element
NAS	National Airspace System
NextGen	Next Generation Air Transportation System
TBFM	Time-Based Flow Management
TMI	Traffic Management Initiatives
TRACON	Terminal Radar Approach Control
WACD	Weibull Autoregressive Conditional Duration

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