Estimation and Comparison of the Impact of Single Airport Delay to the National Airspace System using Multivariate Simultaneous Models

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Abstract— The U.S. air transport as we all know is under significant stress with frequent delays and congestion. Airports are considered as bottlenecks of the National Airspace System (NAS).The major causal factors of flight delay at one airport are over-scheduling, en-route convective weather, reduced ceiling and visibility around airports, and upstream delay propagation. Meanwhile, the delay occurred at this airport will be passed on to other airports in the NAS. Hence, to optimally allocating resource for airport capacity expansion, it needs to quantify the impact of single airport delay to the NAS and vice versa. This research explores the methodology to analyze not only airport delay impact to the NAS, also explore if the delay spillover is widely dispersed across 34 OEP airports or more concentrated using multivariate simultaneous regression models. Three stage least square (3SLS) is used to regress the models and obtain coefficients for the multivariate equations.

Keywords-Airport delay; NAS delay; delay propagation; macroscopic; 3SLS

I. INTRODUCTION

Airport congestion and delay has been the focus of intense research since last few decades. Many major airports in U.S. have significant delay problems due to increased air passenger demand. According to the Department of Transportation's Bureau of Transportation Statistics (BTS) only 79.10% of arrivals were on time from October 2008 to October 2009 [1]. The causes of flight delays include air carrier delay, late arriving, the National Airspace System (NAS), security, and extreme weather. Among these causes, the delays due to aircraft arriving late account for more than 30 percent of total flight delays. As a result of the network structure of the NAS, delay at one airport is likely to affect delays at other airports.

The NAS is a complex system comprising of a large number of airports. It is affected by unexpected events such as adverse weather, equipment outages, aircraft maintenance problem, airline crew issues, and others. All these factors make the NAS a complex and stochastic system. The Next Generation Air Transportation System (NextGen) envisions a highly efficient NAS by 2018 [2] when the total flight delay will be reduced by 30 to 40 percent in comparison to a do-nothing scenario. There are a number of ways that need to be explored and implemented before achieving such a goal: adding or extending runways, developing innovative technologies and procedures, etc. All these alternatives require enormous capital investment. One of the five-year plans that regulates the NAS modernization projects, known as Federal Aviation Administration's Capital Investment Plan (CIP), intended to invest about $16.6 billion from 2010 to 2014 in projects that modernize the existing system, increase airspace capacity, and introduce new technologies to achieve the planned NextGen capabilities [3]. Considering the airport capacity expansion, for optimally allocating resource, there is a need to quantify, not only the local benefits of expansion, but also the advantages of the expansion to the system. From an air transportation planning and policy point of view, sufficient tools are needed to test the system-wide effects of such investment activities and help further strategic planning.

Various researchers have tried to understand the microscopic perspective of delay propagation (Beatty et al. [4], Schaefer and Millner [5], Schaefer et al. [6] and Ahmad Beygi et al. [7]). Nevertheless, their studies capture details of only a few components of the NAS such as specific airports, sectors, or individual flights, but fail to reflect the system overall. A former research done by Zhang and Nayak [8], captures the delay propagation phenomena from a macroscopic point of view. It used multivariate simultaneous-equation regression model to study the impact of single airport delay to the system and vice versa [8]. Specifically, we applied our model to Chicago O' Hare International Airport (ORD) and LaGuardia Airport (LGA). These two airports have attracted enormous attention for significant and persistent delays. The research explored causal factors of the delays at these two airports and compared their system-wide impacts. The estimated results quantified the interdependency between flight delay at an individual airport and other 34 Operational Evolution Partnership (OEP) airports taken together as the NAS. Scenarios were also constructed to analyze how capacity improvements or new demand management strategies at those two airports would affect the performance of the rest of the NAS.

This research presents a macro perspective and proposes not only to investigate the impact of single airport delay to the NAS, but also to explore how the delay spillovers is widely dispersed across the (OEP) 34 airports (see Appendix). Causal factors of average daily arrival delays are explored and multivariate equations are developed for all the airports under consideration along with the NAS. The average daily-arrival delay is the dependent variable in the equation for each airport and the NAS, while it is also taken as an independent variable in the equations of other airports and the NAS. The estimated coefficients can be interpreted as the marginal effect of delay increase of that airport to the other airports or the NAS. This type of model is widely used in economics and business management research studies. We can use the three stage least square (3SLS) method to regress the model.

The remainder of the paper is organized as follows: Section 2 summarizes existing literature on delay propagation and discusses factors affecting delay. Section 3 specifies multivariate simultaneous equations and 3SLS method. Section 4 presents a summary of the results. Section 5 concludes the study and provides suggestions for future research studies.

II. LITERATURE REVIEW

Beatty et al. [4] developed the concept of a delay multiplier for understanding the effect of initial flight delay on an airline's operating schedule. They assumed that various airline resources such as crew members, aircraft, passengers, and gate space affect flight delay. The delay multiplier was used to determine all potential downstream flight delays connected to that initial flight. Their research concludes that the existence of a delay multiplier is due to the branching nature of crew and aircraft sequences. The research estimated the delay propagation from one airport to the other based on the connectivity of airline's operating resources and its schedule.

Delay propagation has also been studied by Schaefer and Millner [5] using the detailed policy assessment tool. They modeled the propagation of delay throughout airports and airspace sectors given inputs such as air traffic demand and airport capacities. They synthesized aircraft assignment given the air traffic data from Official Airline Guide (OAG) and then used the information to simulate delay propagation according to departure and arrival queues between origin and destination airports. Three airports were analyzed using several combinations of Visual Meteorological Conditions (VMC) and Instrument Meteorological Conditions (IMC) when capacities reduced due to inclement weather. The results show that the delay augments with prolonged duration of IMC at the airports. They also concluded that although the propagation effect for the first leg was significant, it diminished along each subsequent leg.

Further research by Schaefer et al. [6] developed an analytical model to separate controllable factors that influence delays and their propagation in the NAS from other factors that are random variables in a given scenario. The controllable factors are scheduled and minimum airport turnaround time, slack for airport turnaround time, scheduled and minimum flight time between airports, and fixed flight time allowance, while the variable factors considered in the research were variable airport turnaround time and variable airport flight time. The model analyzed the interaction between fixed and variable delay components at each airport under both VMC and IMC conditions and emphasized the importance of schedule parameters on delay propagation in the NAS. Their study shows that airports with less slack time between flights had more delay.

A recent research by Ahmad Beygi et al. [7] explores a similar observation in terms of slack time between two flights. Their study indicates that the delay of one flight can propagate to disrupt one or many subsequent downstream flights that await the aircraft and crew from the delayed flight. In such case, the presence of well-planned slack between flights is critical for absorbing the disruption.

The studies discussed above attempt to show how common resources and weighted airline schedules can be major causes of delay propagation. These research studies are clear indicators that the issue of delay propagation at airports is prevalent.

A macroscopic research by Diana [9] proposed a methodology to compute delay propagation from airports based on the Discrete Fourier Transform (DFT). The airports sampled in his study vary in terms of location and traffic throughput. The research assumed that the delay propagation is similar as wave propagation where the delays represent signals and the NAS acts as the medium. Airlines anticipate delays and build precautionary buffer in their schedule to absorb the propagation effects. In his study, he applied the delay concept in airline on-time performance, i.e. only arrival flights with more than fifteen minutes delay past schedule are considered as delayed flights. Diana tried to investigate whether market concentrated airports (i.e. with higher traffic throughput) have more delay propagation effects than less concentrated airports. The outcomes shows that, when delay propagation is considered as a signal through the system, it is not dependent on the degree of market concentration

A recent study done by Laskey et al. [10] takes into consideration the dynamic aspects of flight delay, such as weather effects, wind speed, flight cancellations, and others, to estimate delay propagation in the NAS. They used Bayesian Networks (BN) to quantitatively analyze major factors affecting each delay component and the relationship among the delay components. In their study, flight arrival delay was decomposed into Gate-In Delay, Turn Around Delay, Gate-Out Delay, Taxi-Out Delay, Airborne Delay, and Taxi-In Delay, each of which was considered as a dependent variable for that phase of the flight, with delays from previous phases as independent variables. The principal objective of this research was to estimate the impact of changes in tactical decisions and policies with respect to the ground delay program (GDP), rescheduling, and cancelled flights on delay in the system. Nevertheless, only three months of data were used to identify the critical phase of the flights from ORD and Hatrsfield-Jackson Atlanta International Airport (ATL).

Hansen and Zhang [11] devised a macroscopic technique to study the delay propagation in the NAS. They studied the operational performance at LGA under different demand management regimes using multivariate simultaneous-equation regression model. The outcome of that research shows that, according to historical data from 2000 to

2004, the increase in one minute average-daily-arrival delay at the LaGuardia when compared to airline schedule causes an increase in the average-daily-arrival delay at non-LGA airports by 1.7 minute [4]. The research indentified various factors causing arrival delay at LGA and non-LGA airports and estimated the impact of each of these factors on the total delay.

Our study seeks to extend our previous research, as mentioned in the Introduction, by estimating the interaction between flight delay at one single airport and delay at the other 34 OEP airports and the rest of the NAS. This study quantifies the performance improvement due to capacity expansion and demand management strategies in terms of reducing congestion and delay while controlling for other factors.

III. METHODOLOGY

Multivariate simultaneous equation regression model is a form of statistical model with a set of multivariate equations where the dependent variable in one equation could be independent variable in other equations. In addition, the error terms in the equations could be correlated. This type of model is widely used in economics and business management research studies. In our study, multivariate simultaneous equations are generated for each of the 34 OEP airports excluding Honolulu International Airport (HNL). Additionally, a separate equation is included for the delay in the rest of the NAS by combining all the remaining ASPM77 airports together. As shown in Fig. 1, equations for a single airport share the similar set of independent variables while the NAS contains different variables. The error terms of all the equations are correlated to each other.

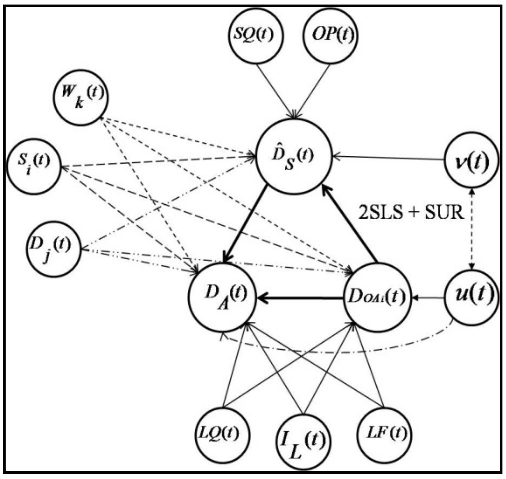


FIGURE 1 Interactions between a Single Airport and rest of the NAS

Three stage least square (3SLS) method can be used to regress the model and obtain coefficients for the multivariate equations. 3SLS combines two statistical techniques, one is the two stage least square (2SLS), and the other seemingly unrelated regression (SUR). In the first stage of 2SLS, each endogenous covariate in the equations of interest is regressed on all of the exogenous variables in the model, including both exogenous covariates in the equation of interest and the excluded instruments. The predicted values from these regressions are obtained. In the second stage, the coefficients in the equations of interest are estimated by regression, except that in this stage each endogenous covariate is replaced with the predicted values from the first stage. SUR is an extension of linear regression model allowing correlated errors between equations. It is a way of improving the efficiency of estimation equations jointly as it provides consistent estimates for linear regression models when explanatory variables are correlated with the error term.

Model variables

Most of the model variables are defined in an earlier paper however; we refined the explanatory variables given the new and extended dataset. The data used in this study is the Aviation System Performance Metric (ASPM) data at 77 airports from 2000 to 2008. For each OEP airport and the rest of the NAS, the average daily arrival delay is a function of average arrival delay at other airports, deterministic queuing delay caused by the over-scheduling or supply-demand imbalance due to capacity deficiency, adverse weather, and flight operations together with dummy variables indicating the seasonal and yearly effects.

Average Daily Arrival Delay

Average daily arrival delay represents the dependent variable in our model. This delay is defined as scheduled daily arrival delay for all ASPM arrivals based on the Official Airline Guide (OAG). Only arrival delays are used as the delay metric, as it is observed that there is a high correlation between arrival and departure delay for both individual airports and the NAS.

Deterministic Queuing Delay

Deterministic queuing delay indicates the operational demand and supply relationship at the airport. The arrival count is the actual number of arrivals at the airports in 15 minutes, which is restricted by the number of flights need to land and airport arrival rate (AAR) during the same time period, In another words, if the number of flights waiting to land is larger than the AAR rate, then the arrival count is the AAR rate, otherwise, the arrival count is the number of flights need to land The cumulative flight demand in a quarter hour is the remaining scheduled arrival demand until the end of the quarter hour [11]. Fig. 2 shows that the arrival count curve is always less than arrival demand since arrival counts are either restricted by arrival demand or the capacity of the system. The daily average queuing delay at an airport is calculated by dividing the area between the curves, which is known as total queuing delay, by the total number of arrivals at the airport for that day [11]. The same definition applies to the NAS model, considering arrivals at all the remaining ASPM77 airports together.

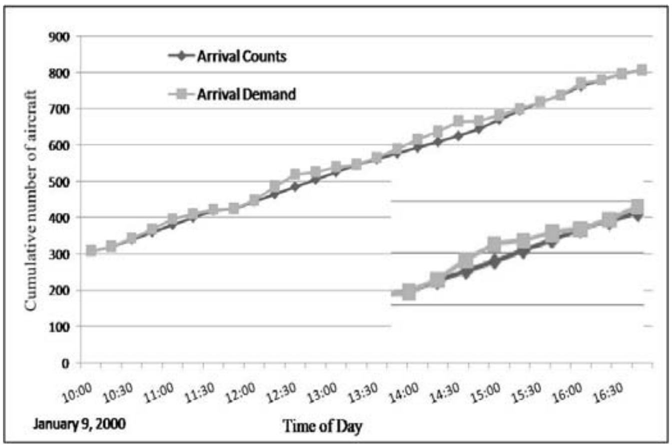


FIGURE 2 Queuing diagram of arrivals at ORD

Adverse Weather
Adverse weather has always been one of the important factors causing delay. In the NextGen environment, new technologies and procedures are being developed to mitigate poor weather conditions [2]. The model captures the adverse weather effects in two ways: convective weather index and IMC ratio. First, convective weather is integrated into the model by dividing the U.S.A. into regions of 10 degrees latitude by 10 degrees longitude. For each region, the proportion of weather stations reporting thunderstorms is obtained from the Surface Summary of Day database maintained by the National Oceanographic and Atmospheric Administration (NOAA). Thus, the convective weather index for a particular region is calculated as the ratio of the number of stations reporting thunderstorms by the total number of stations in the same region. Secondly, the IMC ratio is calculated as the proportion of the day in which the airport was under IMC conditions.

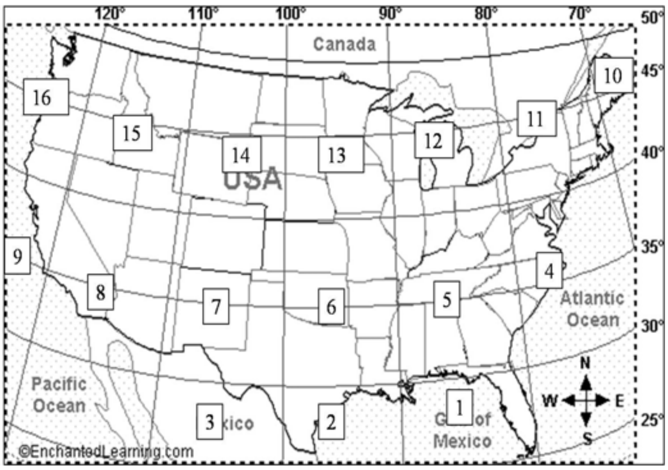


FIGURE 3 USA Weather Regions

Passenger Load Factor
Individual airport models includes monthly passenger load factor as one of the explanatory variable. It is the monthly average ratio of the number of passengers by the number of seats available at the airport under consideration. It is assumed that higher passenger load factor leads to longer average daily arrival delay since it causes uncertainty to smooth daily operations.

Total Flight Operations
The NAS model also contains total flight operations as one of the variables. It captures the effects of total traffic volume on the delay in the NAS. This variable also accurately explains the congestion period in the system.

Seasonal and Yearly Dummy Variables
Dummy variables are introduced to indicate seasons and different years from 2000 to 2008 among which year 2001 has been divided as before and after 9/11 event.

A. Model 1 for an individual airport

The model for an individual airport decomposes average daily delay into components related to different delay casual factors. The explanatory variables include average arrival deterministic queuing delay, average observed arrival delay at other airports, adverse weather, seasonal effects, yearly dummy variable, passenger load factor, and the others.

$$D_A(t) = \alpha_A + \beta_1 D_S(t) + \beta_2 D_{OAi}(t) + \beta_3 LQ(t) + \beta_4 LQ^2(t) + \beta_5 LF(t) + \beta_6 IA(t) + \beta_7 IA^2(t) + \sum_k \lambda_{kA} W_K(t) + \sum_i \omega_{iA} S_i(t) + \sum_i \theta_{jA} D_j(t) + v(t) \quad (1)$$

B. Model 2 for the rest of the NAS

The model for the NAS decomposes average daily delay at rest of the airports that excludes 34 OEP airports. The explanatory variables include variable delays at individual airports, convective weather, total operations, seasonal effects, yearly dummy variable, and other factors.

$$D_S(t) = \alpha_S + \gamma_1 OP(t) + \gamma_2 D_{OAi}(t) + \gamma_3 SQ(t) + \sum_k \lambda_{kS} W_K(t) + \sum_i \omega_{iS} S_i(t) + \sum_i \theta_{jS} D_j(t) + u(t) \quad (2)$$

The notations in the above two models are described as follows:
$D_A(t) =$ Average observed arrival delay against schedule at individual airport on day t;
$D_{OAi}(t) =$ Average observed arrival delay against schedule at other individual airport (i) on day t;
$D_S(t) =$ Average observed arrival delay at airports other than LGA or ORD on day t;
Pred_$D_S(t) =$ Predicted average observed delay at rest of the NAS airports on day *t* (not shown in the above listed models, obtained from the first stage of 3SLS and used in the second stage);
$LQ(t) =$ Average arrival deterministic queuing delay at individual airport on day t;

$LF(t)$ = Passenger load factor at the airport on day t;
$IA(t)$ =Daily IMC ration recorded at individual airport on day t;
Pred_$D_A(t)$ = Predicted average observed delay at individual airport on day t; (not shown in the above listed models, obtained from the first stage of 3SLS and used in the second stage);
$OP(t)$ =Total operations (arrivals) of the system on day t;
$SQ(t)$ =Weighted average arrival deterministic queuing delay of the system on day t;
$W_K(t)$ =Weather index of region k on day t;
$S_i(t)$ =Seasonal dummy variable, set to 1 if daily arrival delay is observed in quarter i and 0 otherwise;
$D_j(t)$ =Yearly Dummy Variable, set to 1 if daily arrival delay is observed in year j and 0 otherwise;
$v(t)$, $u(t)$ = Stochastic error terms; and
$\alpha, \beta, \lambda, \omega, \theta,$ and γ are coefficients.

IV. ESTIMATION RESULTS

The 3SLS method has been used to estimate the coefficients in the simultaneous equation models. The estimated coefficients for average queuing delay for most of the airports except PIT, MEM, SAN and TPA airports indicate that supply and demand imbalance is likely to be a major contributing factor to average daily arrival delays. However, the negative coefficient for the quadratic term of average queuing delay shows that this factor reduces as average queuing delay increases. This study explores the delay propagation from other airports and the rest of the NAS to an individual airport. The estimation results show that the other airports around the same geographical region or the other airports operating as a hub for the same carrier contribute significantly on the delay at the individual airport. For instance, the airports significantly affect the arrival delay at ATL are CLT, CVG, MEM, BWI and MCO, which are all located in the eastern part of the country. Similar regional phenomena can be observed and summarized in Table 1. Counter-intuitively, several airports have negative delay propagation effects on some other airports. For example, the delay increase at LGA will reduce the delay at JFK, MCO, STL, DTW, and CLT. The IMC ratio is likely to impact the delay at almost all the airports except PIT. Most of the airports are affected significantly by the convective weather index in the same region where they are located except BOS, CVG, LAS, MIA, PDX, SLC and SAN. It is also observed that a few airports like DEN, BWI and MEM are affected by thunderstorms occurring at destinations. In addition, convective weather at region 2 and 6 which represent southern states contribute considerably to delay at the rest of the NAS airports.

As long as the weather pattern is captured by convective weather index and IMC ratios, seasonal dummy variables in the model only reflect the seasonal difference of airline scheduling. The estimates for the seasonal effect show that their impact on delay is very small in comparison to other factors. Interestingly, for most of the airports, the winter seasonal effect shows highest amount of delay as compared to other seasons. However for the airports in the southern parts of the country like MCO, FLL, ATL, TPA and LAS, delays are higher during spring. The results from yearly dummy variables have a large impact on average daily arrival delay. The estimated coefficients for the dummy variables provide a better perspective on how delays vary in comparison to different time periods. According to FAA, 34 OEP airports are categorized into different regions (different from the convective weather regions that we have defined earlier) [12]. The trends of average arrival delay for all the airports along with the NAS are shown in Fig. 4 to 11. Fig. 4 shows that the average arrival delays at all the airports in ASO region, except MEM and MIA, decreased from 2000 to 2005 but then increased in 2007. At MIA, average daily arrival delay increased continuously from 2000 to 2008. In Region AWP, as shown in Fig. 5), the delay at LAX and SFO decreased drastically after 9/11 and slowly approached the level of pre 9/11 in 2006. For LAS and PHX in the same region, however, the delay increased immediately after 9/11. Fig. 6 shows the delay trends of the airports in ANM region, which comprises of airports in the north-west of the country. The average arrival delay at those airports was higher in 2007, but still lower than the pre 9/11 level.

The north-central part of the U.S. is represented by AGL region (Fig. 7), which consists of many connecting airports for east-west air traffic. The arrival delay at most of the airports reduced after 9/11 and then increased gradually afterwards. Nevertheless, the delay at MDW airport has significantly reduced from 2000 to 2008, except a rise-up in 2006. The ASW region (Fig. 8) consisting of airports from Texas state had arrival delay reaching its peak in year 2007-08. The north-eastern part of the country that has a few of the world's busiest airports is represented by AEA region (Fig. 9). This region consists of the largest number of airports as compared to other regions. For all the airports, except IAD, the average arrival delay reduced after 9/11, slowly increasing thereafter and reaching its peak in 2007. The average arrival delay at rest of the airports (Fig. 10 and Fig. 11) reduced after 9/11 and reached its peak in 2007.

V. CONCLUSION

Airport delay has always been a major problem for the aviation industry. Most previous studies estimate the delay propagated through an individual flight from an airport to the system. This research illustrated the effectiveness of applying multivariate simultaneous equation model to study delay propagation from a single airport to other airports and to the rest of the system, and vice versa. The model developed for airports takes into account all the delay causal factors mentioned earlier and can include more in future models.

TABLE 1 Interactions between Different Individual Airports and the NAS

Individual Airport	Airports Contributing to Average Arrival Delay	Airports Reducing Average Arrival Delay
ATL	CLT (0.264), CVG (0.220), MEM (0.260), BWI (0.160), MCO (0.229) and NAS(0.324)	MIA (-0.177)
BOS	ATL (0.051), CLT (0.262), CVG (0.218), MEM (0.249) and NAS (0.302)	MIA (-0.182)
BWI	ATL (0.042), EWR (0.131), PHL (0.094), IAD (0.093)	
CLE	DTW (0.115), EWR (0.088), PIT (0.146) and NAS (0.472)	
CLT	ATL (0.070), PHL (0.107), PIT (0.148) and NAS (0.3220)	LGA (-0.086)
CVG	ATL (0.051), ORD (0.042), PIT (0.176) and NAS (0.235)	
DCA	ATL (0.038), IAD (0. 142), PHL (0.154) and NAS (0.195)	
DEN	ORD (0.039), PDX (0.228), PHX (0.159), SLC (0.162), DTW(0.090)	BOS (-0.009), CLE (-0.125)
DFW	IAH (0.087), PHX (0.145) and NAS (0.224)	BOS (-0.019)
DTW	EWR (0.080), FLL (0.141), IAD (0.131), ORD (0.060) and NAS (0.228)	BOS (-0.014), BWI (-0.174), LGA (-0.087)
EWR	CLT (0.248) and NAS (1.210)	MSP (-0.089), SAN (-0.354)
FLL	EWR (0.108), MCO (0.413), PHL (0.111), TPA (0.355)	
IAH	NAS (0.291)	
IAD	EWR (0.088), PHL(0.094) and NAS (0.479)	SAN (-0.265), DFW (-0.066)
JFK	BOS (0.050), EWR (0.277), FLL (0.198)	LGA (-0.130)
LAS	DEN (0.084), LAX (0.114), PHX (0.233), SFO (0.055), SLC (0.100)	BOS (-0.016)
LAX	LAS (0.139), MEM (0.110), PHX (0.129), SFO (0.106), SLC (0.083)	BOS (-0.013)
LGA	EWR (0.385) and NAS (1.574)	BOS (-0.094)
MDW	DTW (0.188), ORD (0.264), PHL (0.089) and NAS (0.341)	
MEM	ATL (0.053), CVG (0.149), MSP (0.072), ORD (0.037) and NAS (0.383)	BWI (-0.149)
MIA	EWR (0.068), FLL (0.197), MCO (0.275), TPA (0.210)	
MSP	DTW (0.118), ORD (0.041), SLC(0.121) and NAS (0.216)	
ORD	DTW (0.331), MDW (0.843), MSP (0.238) and NAS (0.562)	BWI (-0.326)
PDX	DEN (0.456), LAS (0.049), SEA (0.292), SFO (0.056), SLC (0.117)	
PIT	DTW (0.317), MDW (0.781), MSP (0.219), ORD (0.425)	
PHL	CLT (0.22), EWR (0.099) and NAS (0.661)	
PHX	DEN (0.077), LAS (0.107), SLC (0.087)	BOS (-0.013), PDX (-0.177)
SAN	EWR (0.052), LAS (0.217), LAX (0.177), PHX (0.162), SFO (0.089), SLC (0.091),	BOS (-0.014), BWI (-0.105)

	STL (0.043)	
SEA	FLL (0.091), PDX (0.599)	BOS (-0.011)
SFO	EWR (0.129) and NAS (0.393)	BOS (-0.090)
SLC	DEN (0.096), FLL (0.108), PDX (0.268), PHX (0.091), SFO (0.034)	BOS (-0.016)
STL	EWR (0.105), ORD (0.084), PHX (0.115) and NAS (0.170)	BOS (-0.025), LGA (-0.094)
TPA	ATL (0.069), CVG (0.095), EWR (0.071), FLL (0.131), MCO (0.146), PHL (0.075)	BOS (0.010)
NAS (System)	ATL (0.031), CVG (0.068), EWR (0.065), LAS (0.050), MEM (0.113), ORD (0.029), PHX (0.100), SLC (0.059), STL (0.043)	BOS (-0.006)

The model estimates the effect of each of these factors using the 3SLS method. This method is generally used to deal with the bidirectional relationship that exists between dependent and independent variables and suitable for the equations with correlated error terms. The estimated results help quantify the interdependency between flight delays at different airports and the NAS.

The regression results show that queuing delay and adverse weather are major delay causal factors at most of the studied airports. Passenger load factor is an important factor at some of the hub airports like MDW and MEM but not others. Airports located in same geographical regions had more interactions than others. Major airports like ATL, ORD, PHX and EWR had more impact on average arrival delay than other airports. BOS, MIA and BWI had least impact on arrival delay at other airports. The graphical representation for different time periods from the year 2000 to 2008 demonstrates the significantly delay variation. Most of the airports, with a few exceptions, had their delay reduced after 9/11 and gradually increased back to pre 9/11 lever with a peak in 2007.

As the next step of this research, we are exploring more explanatory variables such as capacity ratio, runway configurations, wind speed, demand management programs for all the airports and conduct more experiments on the specification of the model. To improve the efficiency of the model we also need to check the availability of some surrogates for our existing variables like passenger load factor, IMC ratio, etc. We plan to look into different delay definitions as well. Depends on the implementation of the model, arrival delay could be measured according to airline schedule or flight plan. We also need to find out the causes for delay at each specific individual airport. We would also like to explore how the delay in regional airport system affects other airports and the rest of the NAS. A good example will be the New York regional airport system containing LGA, EWR, and JFK.

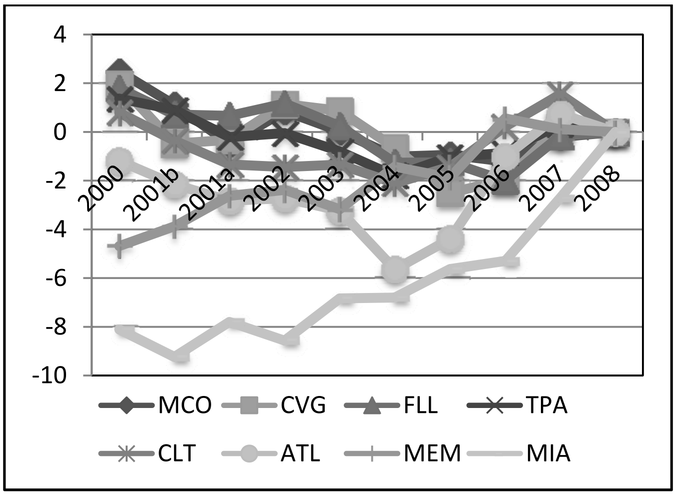


FIGURE 4 Airport Arrival Delay from 2000-2008 for ASO Region

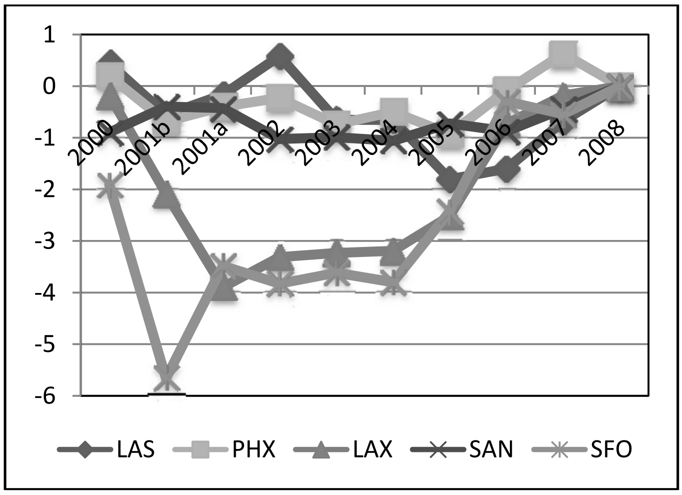
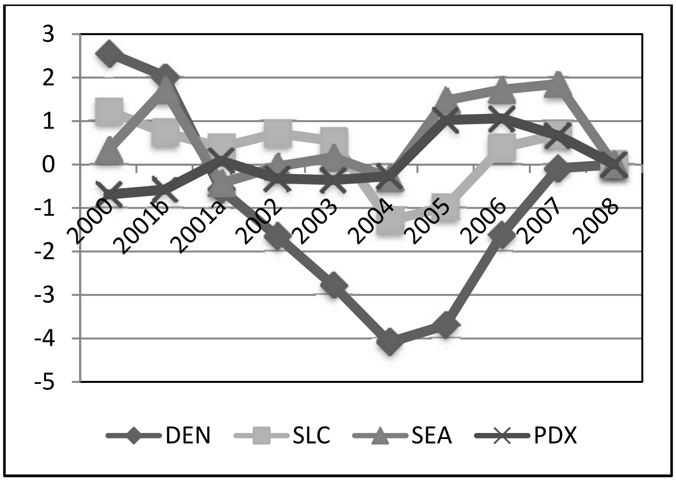


FIGURE 5 Airport Arrival Delay from 2000-2008 for AWP Region



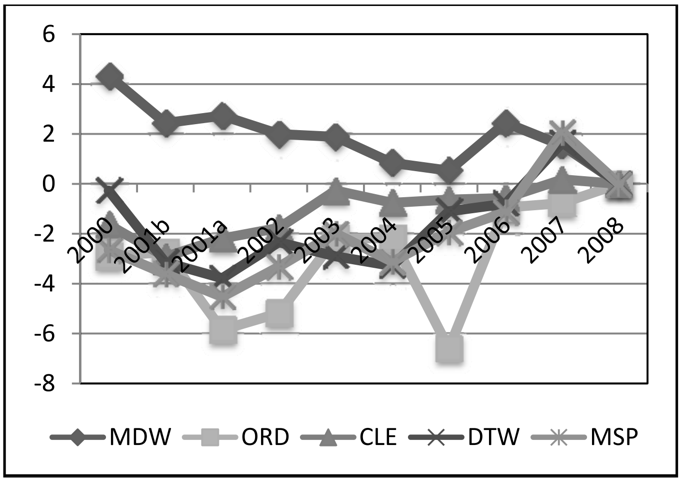
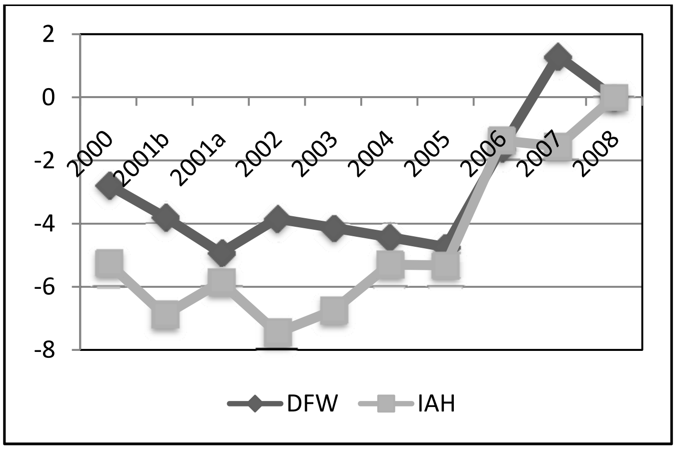


FIGURE 6 Airport Arrival Delay from 2000-2008 for ANM Region

FIGURE 7 Airport Arrival Delay from 2000-2008 for AGL Region



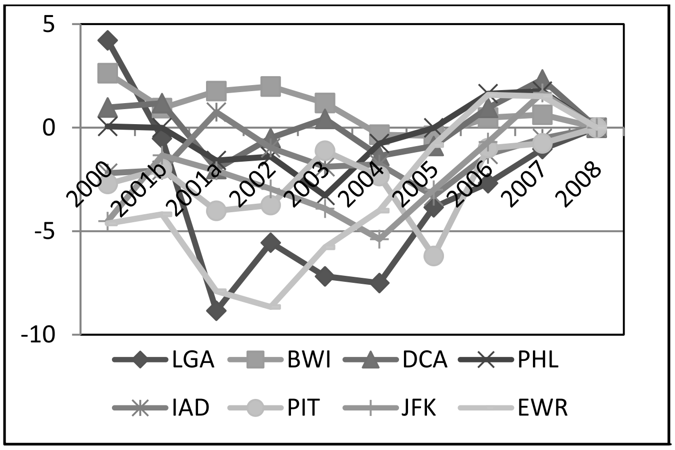
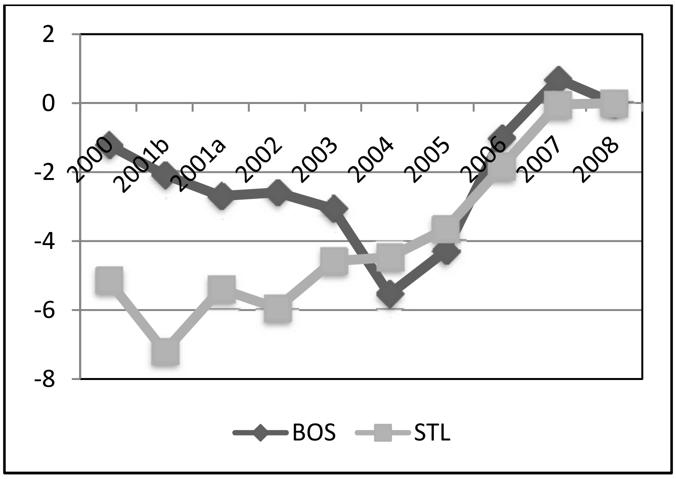


FIGURE 8 Airport Arrival Delay from 2000-2008 for ASW Region

FIGURE 9 Airport Arrival Delay from 2000-2008 for AEA Region



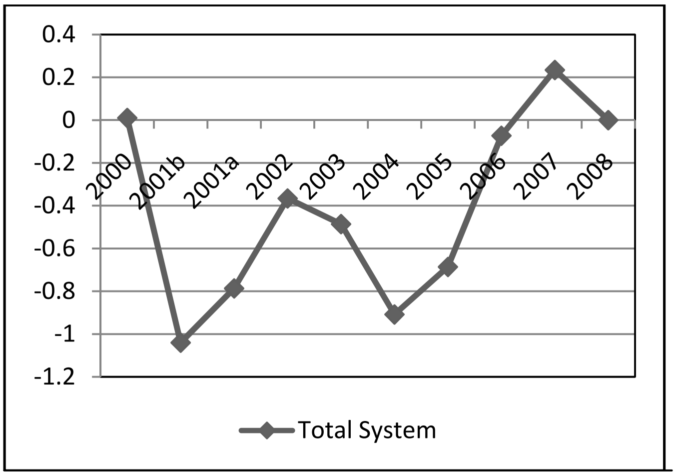


FIGURE 10 Airport Arrival Delay from 2000-2008 for ANE (BOS) and AAL (STL) Regions

FIGURE 11 Airport Arrival Delay from 2000-2008 for NAS

APPENDIX

List of Abbreviations related to different OEP airports

ATL	Atlanta Hartsfield International
BOS	Boston Logan International
BWI	Baltimore-Washington International
CLE	Cleveland-Hopkins International
CLT	Charlotte/Douglas International
CVG	Cincinnati-Northern Kentucky
DCA	Ronald Reagan National
DEN	Denver International
DFW	Dallas-Fort Worth International
DTW	Detroit Metro Wayne County
EWR	Newark International
FLL	Fort Lauderdale-Hollywood International
IAD	Washington Dulles International
IAH	George Bush Intercontinental
JFK	New York John F. Kennedy International
HNL	Honolulu International
STL	Lambert St. Louis International
LAS	Las Vegas McCarran International
LAX	Los Angeles International
LGA	New York LaGuardia
MCO	Orlando International
MDW	Chicago Midway
MEM	Memphis International
MIA	Miami International
MSP	Minneapolis-St Paul International
ORD	Chicago O'Hare International
PDX	Portland International
PHL	Philadelphia International
PHX	Phoenix Sky Harbor International
PIT	Greater Pittsburgh International
SAN	San Diego International Lindbergh
SEA	Seattle -Tacoma International
SFO	San Francisco International
SLC	Salt Lake City International
TPA	Tampa International

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