Macroscopic Tool for Measuring Delay Performance in National Airspace System

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Airline delays lead to a tremendous loss of time and resources and cost billions of dollars every year in the United States. To explore solutions for reducing delay, it is essential to understand factors causing flight delays and also the network impact of delays at one airport in the National Airspace System (NAS). For air transportation planning and policy purposes, this study concentrates on providing answers from a macroscopic point of view without being distracted by volatile operational details. A set of multivariate equations is proposed to model daily average arrival delay at one airport, and another for the rest of the NAS. The model for the single airport considers independent variables such as deterministic arrival queuing delay, delay at other airports in the NAS, adverse weather (convective and local), and different demand management regimes. The model for the rest of the NAS considers arrival delay as a function of deterministic arrival queuing delay, arrival delay at the single airport, adverse weather (convective and local), and other factors. Observation of the interactions between these two models shows that they can be regressed with an econometric technique: two-stage least squares. This macroscopic framework of delay impact analysis can be used to investigate the network effect of capacity improvement or new demand management strategies at a single airport. Hypothetical scenarios are generated and the systemwide delay reduction is calculated. This is a powerful decision support tool for stakeholders to use in deciding how to allocate resources optimally and to reduce delays.

U.S. air transportation demand has increased dramatically since its advent in the early 20th century. The geographical extent of the country has made air transport one of the preferred means of transportation. However, extensive use of air transportation has caused frequent airport delays that lead to losses worth billions of dollars. About 70% of airline operations are served by 35 operational evolution partnership (OEP) airports (*1*). Given the network structure of the National Airspace System (NAS), delay at one airport propagates to others. The traffic concentration at the 35 OEP airports makes their operations highly interdependent. The concepts of the Next Generation Air Transport System (NextGen) envision a highly efficient NAS by 2018 (*2*). It intends to reduce total flight delays by 30% to 40% by 2018 compared with a do-nothing scenario. There are a number of ways that NextGen can achieve the goal, including by the addition or extension of runways at airports or by implementation of innovative technologies and procedures. Both require enormous capital investment. One of the 5-year plans that regulate the NAS modernization projects, popularly known as the FAA Capital Investment Plan, is intended to invest about $16.6 billion (as of April 2009) for projects that modernize the existing system, increase airspace capacity, and introduce new technologies to achieve the planned NextGen capabilities (*3*). From the point of view of air transportation planning and policy, sufficient tools are needed to test the systemwide effect of such investment activities and help further strategic planning.

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Transportation Research Record: Journal of the Transportation Research Board, No. 2177, Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 88–97.
DOI: 10.3141/2177-11

The NAS is a complex stochastic system comprising a large number of airports, aircraft, airlines, passengers, and control centers. Airlines operate with different network structures, such as hub-and-spoke and point-to-point networks. The NAS is affected by unexpected events such as adverse weather, equipment outages, airline maintenance problem, crew sickness, and the like. All these factors make NAS a complicated, random, and undetermined system. Therefore, if too many details in this system are considered, it would be difficult to get a meaningful complete picture. Various researchers in their studies have tried to understand the microscopic perspective of delay propagation. These studies capture details of only a few components, such as specific airport, sector, or individual flight, but fail to reflect the system overall. In comparison, macroscopic research has the ability to cover much larger variations together with the required precision.

The current research models the delay at a single airport and that of the rest of the NAS with multivariate simultaneous equations, taking into account the delay propagation from that single airport to the rest of the NAS and vice versa. This is a model from the macroscopic point of view that can be regressed with econometrics tools, such as the two-stage least squares (2SLS). Chicago (Illinois) O'Hare International Airport (ORD) and New York La Guardia Airport (LGA) were selected as two cases for consideration in this research. These two airports have attracted enormous attention for significant and persistent delays. The research explores causal factors of the delays at these two airports and compares their systemwide impacts. Scenarios are 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.

The remainder of the paper is organized as follows: the next section summarizes existing literature on delay propagation and discusses factors affecting delay. Then there is a discussion of the specifics of multivariate simultaneous equations and 2SLS. What follows is a presentation of a summary of the results and a description of the hypothetical scenario analysis for LGA and ORD. The final two sections conclude the study and provide suggestions for prospective research studies.

PRIOR RESEARCH

Beatty et al. (*4*) developed the concept of a delay multiplier to understand the effect of initial flight delays on an airline's operating schedule. It assumed that various airline resources, such as crews, aircrafts, passengers, and gate space, affect flight delays. The delay multiplier was used to determine all potential downstream flight delays connected to the initial flight. The research of Beatty et al. (*4*) concludes that the existence of a delay multiplier is due to the branching nature of crew and aircraft sequences. The research estimates the delay propagated for each aircraft at the airport.

Flight delay propagation was also studied by Schaefer and Millner (*5*) through the detailed policy assessment tool. Their research models the propagation of delays throughout airports and airspace sectors. It shows that the propagation effect is reduced after each subsequent flight leg. The basic inputs considered in the model were air traffic demand and airport capacities. The model developed flight itineraries to simulate delay propagation from departure and arrival queues between origin and destination airports. Three airports were analyzed by means of several combinations of visual meteorological conditions (VMC) and instrument meteorological conditions (IMC) to include capacity reductions during inclement weather. The results show that the delay increases with increasing duration of IMC at the airport, while the propagation effect for the first leg was significant but diminished after each subsequent leg.

Further research by Schaefer et al. (*6*) developed an analytical model for separating 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 study shows that airports with less slack or allowance time between flights had more delay. The model analyzes the interaction between fixed and variable delay components at each airport under both VMC and IMC conditions and emphasizes the importance of schedule parameters on delay propagation in the NAS. Recent research by AhmadBeygi et al. (*7*) explores a similar model. Their study indicates that each flight delay can propagate to disrupt one or many subsequent downstream flights that await the aircraft and crew of delayed flights. In such cases, 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.

The research most closely related to this paper is that of Laskey et al. (*8*). Their model 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. The study uses Bayesian networks to analyze quantitatively both the major factors affecting each delay component and the relationships among the delay components. In their study, flight arrival delay is decomposed to GateIn Delay, TurnAround Delay, GateOut Delay, TaxiOut Delay, Airborne Delay, and TaxiIn Delay, each considered a dependent variable for that phase of the flight, with delays from previous phases as independent variables. The principal objective of their research was to estimate the impact of changes in tactical decisions and policies with respect to the ground delay program, rescheduling, and cancelled flights on delay in the system. Nevertheless, only 3 months of data were used to identify the critical phase of the flights from ORD and Hartsfield–Jackson Atlanta International Airport (ATL) in Georgia.

Hansen and Zhang (*9*) devised a macroscopic technique to study the delay propagation in the NAS. They studied the operational performance at LGA under different demand management policies by means of multivariate simultaneous regression models. The current study seeks to extend this research by estimating the interaction between flight delays at one airport and delay for the rest of the NAS. It is also able to produce decomposition of delays according to causal factors for both an individual airport and the NAS. In addition, it tries to predict the systemwide impact of capacity improvement or demand management strategies at a single airport. Both LGA and ORD have become synonymous with delays in recent years. These are highly congested airports with a combined operation of 105,218 flights for 2008, ranking among the highest in the country (*10*). The demand management strategies at LGA and ORD have always been parallel, as shown in Figure 1 (*11*). This study has the ability to quantify the performance improvement due to demand management strategies in relation to reducing congestion and delay while controlling for other factors. Quarter-hourly data from the Aviation System

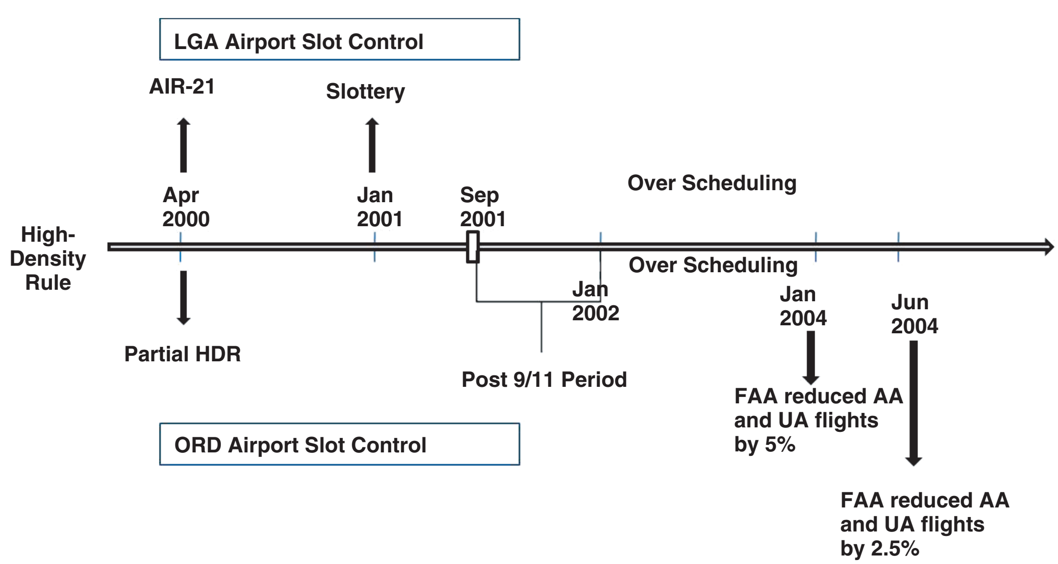


FIGURE 1 Demand management regimes at LGA and ORD airports.

Performance Metrics (ASPM) database, maintained by FAA's Aviation Policy and Plans Office, for the period between January 2000 and June 2004, are used. During this period, numerous demand management strategies were employed at both airports.

The high-density rule (HDR) was introduced at LGA and ORD in 1968. The HDR period at LGA was characterized by limiting the hourly slots to 68 between 6:00 a.m. and midnight. The slots were initially regulated by a scheduling committee composed of representatives from different airlines. In 1986, the scheduling committee was replaced by use-it-or-lose-it and buy–sell rules (*12*). However, with no airline willing to sell its slots, FAA granted 42 slot exemptions for various air services to LGA, especially for ones that were new-entrant airlines or essential air services. As a result, by 1997, 30 new-entrant exemptions were approved for LGA (*12*). In April 2000, a demand management strategy called AIR-21 was introduced to eliminate slot control. During AIR-21, delays increased dramatically due to an increasing number of requests for slot exemptions. To overcome such delay, the FAA quashed the AIR-21 slot exemptions it had already granted and redistributed some of these exemptions by lottery ("slottery"). It also capped the number of operations per hour for commercial flights to 75 from the initial 100 under AIR-21. The terrorist attacks on September 11, 2001 (9/11), affected airport operations in many ways. Beginning in 2002, air traffic increased each following year, leading to a period of overscheduling, and HDR completely expired by 2007 (*12*).

ORD, similarly, has its own demand management regimes affecting air traffic operations in and around the airport. As mentioned earlier, the HDR strategy was also applied at ORD in 1968 and resulted in the slot control phenomenon by major airlines. In the 1990s, 53 new slot exemptions were created at ORD (*12*). Gradually, the HDR strategy was reduced at ORD, and its complete elimination occurred by 2002. The operations at ORD were greatly reduced after 9/11; however, since 2002, a general increase in air traffic has occurred, creating a period of overscheduling, with 100 daily operations more than capacity allowed at ORD. This period of increased operations made delay one of the major problems at ORD and resulted in the FAA negotiating a 5% reduction in American Airlines (AA) and United Airlines (UA) flights in January 2004. However, these vacated slots were quickly taken up by Northwest Airlines and Independence Air, resulting in a further reduction of AA and UA flights in June 2004 by 2.5% to reduce delays (*12*). In August 2004, from a meeting between federal officials and individual airlines, the scheduled arrivals of AA and UA flights were further reduced by 5% during peak hours. Other airlines also agreed to some flight retimings and to limiting the number of scheduled arrivals. Finally, in August 2006, FAA issued a rule limiting flight operations until the completion of the first phase of ORD expansion in 2008 (*13*).

This research has tried to decompose delays at LGA and ORD and to understand their spillover effects in the NAS for these demand management regimes from January 2000 to June 2004.

METHODOLOGY

Multivariate simultaneous equations were developed for both individual airports and the NAS. Both these models were regressed by mean of the 2SLS method, which is an extension of the ordinary least-squares method used generally when models are nonrecursive with a bidirectional relationship between the causal factors and the error terms, as shown in Figure 2*a.* The 2SLS method is a handy technique when the dependent variable of one model could be one of the independent variables of the other model. Figures 2*b* and 2*c* show the use of the predicted value of the average observed arrival delay at the NAS as the independent variable for average observed arrival delay at an individual airport and vice versa. This predicted value was the dependent variable created at the end of the first stage of regression and, along with the other variables, was used in the second stage to regress arrival delays with full models. It was also observed that the errors were heteroscedastic. The autocorrelations, however, were insignificant in this case.

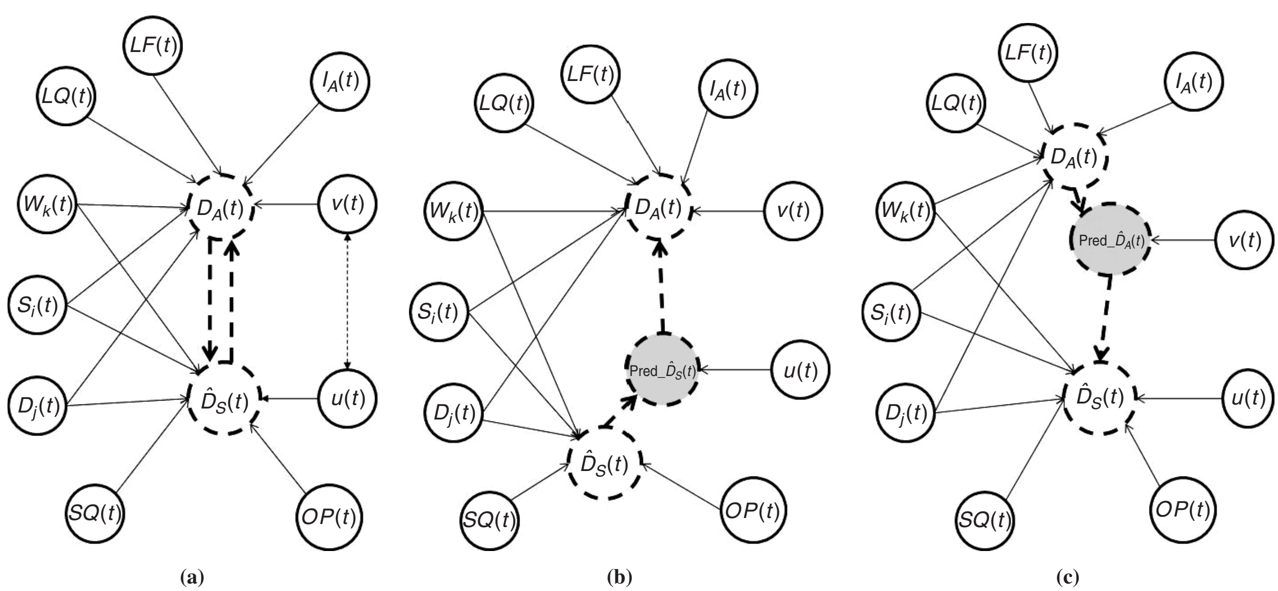


FIGURE 2 Two stage least-squares regression: (*a*) interaction between single airport and rest of NAS, (*b*) two stage least-squares estimates for LGA-ORD, and (*c*) two stage least-square estimates for NAS.

Model Variables

Most of the model variables were comprehensively described in the previous version of this paper (*9*); however, they have been refined by the addition of more explanatory variables that can help capture more of the variance of the data and provide better estimation of systemwide delays given scenarios of different expansion plans of a single airport.

Daily Arrival Delay

Average daily arrival delay is the dependent variable in the model. This delay is defined as scheduled daily arrival delay for all ASPM arrivals on the basis of the *Official Airline Guide*. Only arrival delay is used as the delay metric because there is a high correlation between arrival and departure delays 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 representing supply is obtained as airport-supplied arrival rate from the ASPM data. The cumulative flight demand at the quarter-hour *i* is the sum of scheduled arrival demand subtracted from cancellations until time *i* (*9*). Figure 3 shows that the arrival count curve is always less than the arrival demand because arrival count is 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 delay, by the total number of arrivals at the airport for that day (*9*). The same definition applies to the NAS model and considers arrivals at airports in the NAS except the individual reference airport.

Adverse Weather

Adverse weather has always been one of the important factors causing delay, and many new technologies in NextGen are being developed to negate its effects (*2*). This research introduces adverse weather in two ways, convective weather and IMC ratio. First, for indicating convective weather, the United States is divided into regions of 10° latitude by 10° longitude. For each region, the proportion of weather stations reporting thunderstorms is computed from the Surface Summary of Day database maintained by the National Oceanographic and Atmospheric Administration. From the thunderstorm data, the thunderstorm ratio is calculated as the ratio of the number of stations reporting thunderstorms by the total number of stations.

The second delay metric is the IMC ratio, calculated as the proportion of the day in which the airport was under IMC conditions. It is known that an airport operating under IMC conditions has a lower capacity, which causes more delays, than that operating under VMC conditions.

Passenger Load Factor

A new variable introduced in this research is the monthly passenger load factor. It is the monthly average ratio of the number of passengers

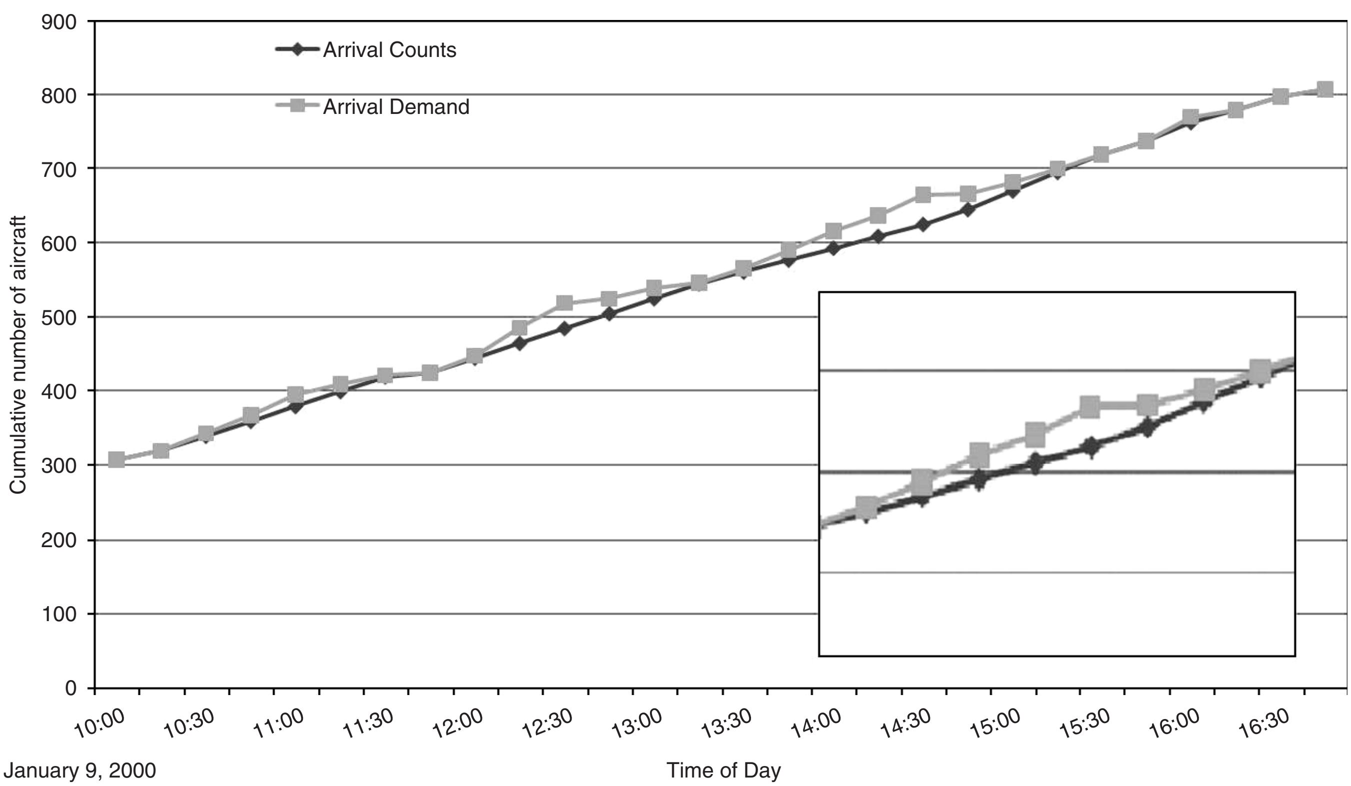


FIGURE 3 Queuing diagram of arrivals at ORD.

by the number of seats available at the airport under examination. It is assumed that a higher passenger load factor leads to longer average daily arrival delay because it causes uncertainty in smooth daily operations.

Total Flight Operations

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

Seasonal and Demand Management Dummy Variables

Dummy variables are introduced to indicate seasons and different demand management regimes.

Model 1 for Individual Airport

The model for the individual airport decomposes average daily delay at LGA or ORD into components related to different delay causal factors. The explanatory variables include average arrival deterministic queuing delay, average observed arrival delay at other airports, adverse weather, seasonal effects, demand management regimes, and other factors.

$$D_A(t) = \alpha_A + \beta_1 \cdot D_S(t) + \beta_2 \cdot \mathrm{LQ}(t) + \beta_3 \cdot \mathrm{LQ}^2(t) + \beta_4 \cdot \mathrm{LF}(t) + \beta_5 \cdot I_A(t) + \beta_6 \cdot I_A^2(t) + \sum_k \lambda_{kA} \cdot W_k(t) + \sum_i \omega_{iA} \cdot S_i(t) + \sum_j \theta_{jA} \cdot D_j(t) + v(t)$$

where

$D_A(t)$ = average observed arrival delay again schedule at individual airport on day t,
$D_s(t)$ = average observed arrival delay at airports other than LGA or ORD on day t,
$\mathrm{LQ}(t)$ = average arrival deterministic queuing delay at individual airport on day t,
$\mathrm{LF}(t)$ = passenger load factor at the airport on day t,
$I_A(t)$ = daily IMC ratio recorded at individual airport 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 to 0 otherwise),
$D_j(t)$ = demand management regime dummy variable (set to 1 if daily arrival delay is observed in time period j and to 0 otherwise),
$v(t)$ = stochastic error term, and
$\alpha, \beta, \lambda, \omega, \theta$ = coefficients.

Model 2 for NAS

The model for the NAS decomposes average daily delay at airports other than the airports under examination (LGA and ORD). The explanatory variables include variable delays at LGA or ORD, convective weather, total operations, seasonal effects, demand management regimes, and other factors.

$$D_S(t) = \alpha_S + \gamma_1 \cdot \mathrm{OP}(t) + \gamma_2 \cdot D_A(t) + \gamma_3 \cdot \mathrm{SQ}(t) + \sum_k \lambda_{kS} \cdot W_k(t) + \sum_i \omega_{iS} \cdot S_i(t) + \sum_j \theta_{js} \cdot D_j(t) + u(t)$$

where

$\mathrm{OP}(t)$ = total operations (arrivals) of system on day t,
$\mathrm{SQ}(t)$ = weighted average arrival deterministic queuing delay of system on day t,
$u(t)$ = stochastic error term, and
γ = coefficient.

Two additional terms not shown in the models but obtained from the first stage of 2SLS and used in the second stage are the following:

- Pred_$D_s(t)$, the predicted average observed delay at airports other than LGA or ORD on day t and
- Pred_$D_A(t)$, the predicted average observed delay at individual airport (LGA or ORD) on day t.

ESTIMATION RESULTS

The regression results from the analyses are shown in Tables 1 and 2. It was assumed that the mean of delay is zero if all the independent variables are zero. The R^2 values from Table 1 clearly indicate that the model captured about 77.41% and 82.42% of the variation in the average daily arrival delay at LGA and ORD, respectively. The estimated coefficient for average queuing delay is 0.235 for LGA and 1.270 for ORD, while for the quadratic term of average queuing delay, the coefficients are negative. Nevertheless, the combined effect of linear and quadratic terms of average queuing delay is positive. It was also found that a 1-min delay at other airports in NAS may cause delay increases of 0.946 and 0.553 min at LGA and ORD, respectively. One of the components of adverse weather, IMC ratio, is the principal factor of delay at both LGA and ORD. For the thunderstorm ratio, however, only specific regions show significant contributions. Region 11, comprising the northeastern part of the United States, is a major delay contributor at LGA; Regions 12 and 13, which include the upper-middle regions of the United States, are delay contributors at ORD. The estimates for the seasonal effect, however, show smaller magnitude compared with other factors. Interestingly, for both airports, the summer seasonal effect shows the least amount of delay compared with other seasons. Significant factors affecting delay are demand management regimes (time period fixed effects). HDR was considered as the base in the regression. These estimates provide a better perspective of different demand management regimes applied for different time periods (Figure 1) and the success of their application in relation to operations and delay reduction.

The delays have been graphically decomposed according to the causal factors, as shown in Figures 4 and 5. For LGA, the delay increased by more than 12 min during the AIR-21 period in comparison with HDR and gradually decreased during the slottery period. The lowest delay was reached post-9/11, when there were fewer air traffic operations, and it slowly increased through 2004. For ORD, the general phenomenon was the same, reaching high delays during partial HDR periods, touching low levels post-9/11, and sharply shooting up in 2004 to more than 2 min. As Figure 4*a* shows, average delay

TABLE 1 Estimation Results of Arrival Delay at Individual Airport (LGA–ORD)

	LGA			ORD		
Variable	Estimate	SE[a]	*p*-Value	Estimate	SE[a]	*p*-Value
LQ(t), average queuing delay	0.235	0.02	<.0001	1.270	0.05	<.0001
LQ$^2(t)$, quadratic average queuing delay at airport	–0.001	0.00	<.0001	–0.007	0.00	<.0001
$D_S(t)$, predicted arrival delay at NAS	0.946	0.08	<.0001	0.553	0.11	<.0001
$I_A(t)$, IMC ratio	24.900	2.68	<.0001	21.717	3.41	<.0001
$I_A^2(t)$, square of IMC ratio	–9.568	2.82	.0007	–9.414	3.73	.0115
LF(t), passenger load factor	0.075	0.02	.0013	0.020	0.03	.4731
$W_K(t)$, thunderstorm ratio						
Region 11	45.280	3.64	<.0001			
Region 12				44.144	3.64	<.0001
Region 13				11.775	2.79	<.0001
$S_i(t)$, seasonal dummy variables						
Quarter 1	–3.832	0.79	<.0001	–1.539	1.35	.2537
Quarter 2	–8.567	0.96	<.0001	–4.622	1.51	.0022
Quarter 3	–6.489	0.96	<.0001	–3.353	1.50	.0252
$D_j(t)$, demand management regimes						
AIR-21	5.122	1.12	<.0001			
Slottery	–1.227	1.17	.2942			
Partial HDR				0.231	2.04	.9271
Post 9/11 period	–10.050	2.09	<.0001	–7.160	2.53	.0047
Year 2002	–3.033	1.14	.0079			
Year 2003	–3.480	1.024	.0007			
Year 2004	–6.101	1.216	<.0001			
Overscheduling				–3.891	1.87	.0374
5% reduction in UA & AA				2.264	1.93	<.2405

NOTE: R^2 = .7741 for LGA, .8254 for ORD.
[a]Standard error.

TABLE 2 Estimation Results of Arrival Delay for NAS

	LGA			ORD		
Variable	Estimate	SE[a]	*p*-Value	Estimate	SE[a]	*p*-Value
SQ(t), average queuing delay	1.176	0.04	<.0001	0.963	0.05	<.0001
$D_A(t)$, predicted arrival delay at LGA–ORD	0.082	0.01	<.0001	0.052	0.00	<.0001
OP(t), total operations (arrivals) in the system	0.001	0.00	<.0001	0.001	0.00	<.0001
$W_k(t)$, thunderstorm ratio						
Region 04	4.010	0.95	<.0001	6.511	0.94	<.0001
Region 05	4.863	0.79	<.0001	5.345	0.78	<.0001
Region 06	5.056	0.61	<.0001	3.623	0.58	<.0001
Region 11	2.495	1.27	.0493	11.682	1.10	<.0001
Region 12	11.572	0.92	<.0001	5.625	1.12	<.0001
$S_i(t)$, seasonal dummy variables						
Quarter 1	0.666	0.47	.1577	0.242	0.48	.6123
Quarter 2	–2.657	0.49	<.0001	–3.275	0.52	<.0001
Quarter 3	–3.163	0.51	<.0001	–3.802	0.53	<.0001
$D_i(t)$, dummy variable for demand management regimes						
AIR-21	2.086	0.61	.0007			
Slottery	0.865	0.61	.1578			
Partial HDR				1.447	0.57	.0111
Post 9/11 period	–0.176	0.78	.8207	–0.795	0.83	.3396
Year 2002	–0.651	0.56	.2416			
Year 2003	–0.768	0.56	.1701			
Year 2004	0.263	0.63	.6773			
Overscheduling				–1.095	0.53	.0383
5% reduction in UA & AA				–1.376	0.67	.0411

NOTE: R^2 = .944 for LGA, .941 for ORD.
[a]Standard error.

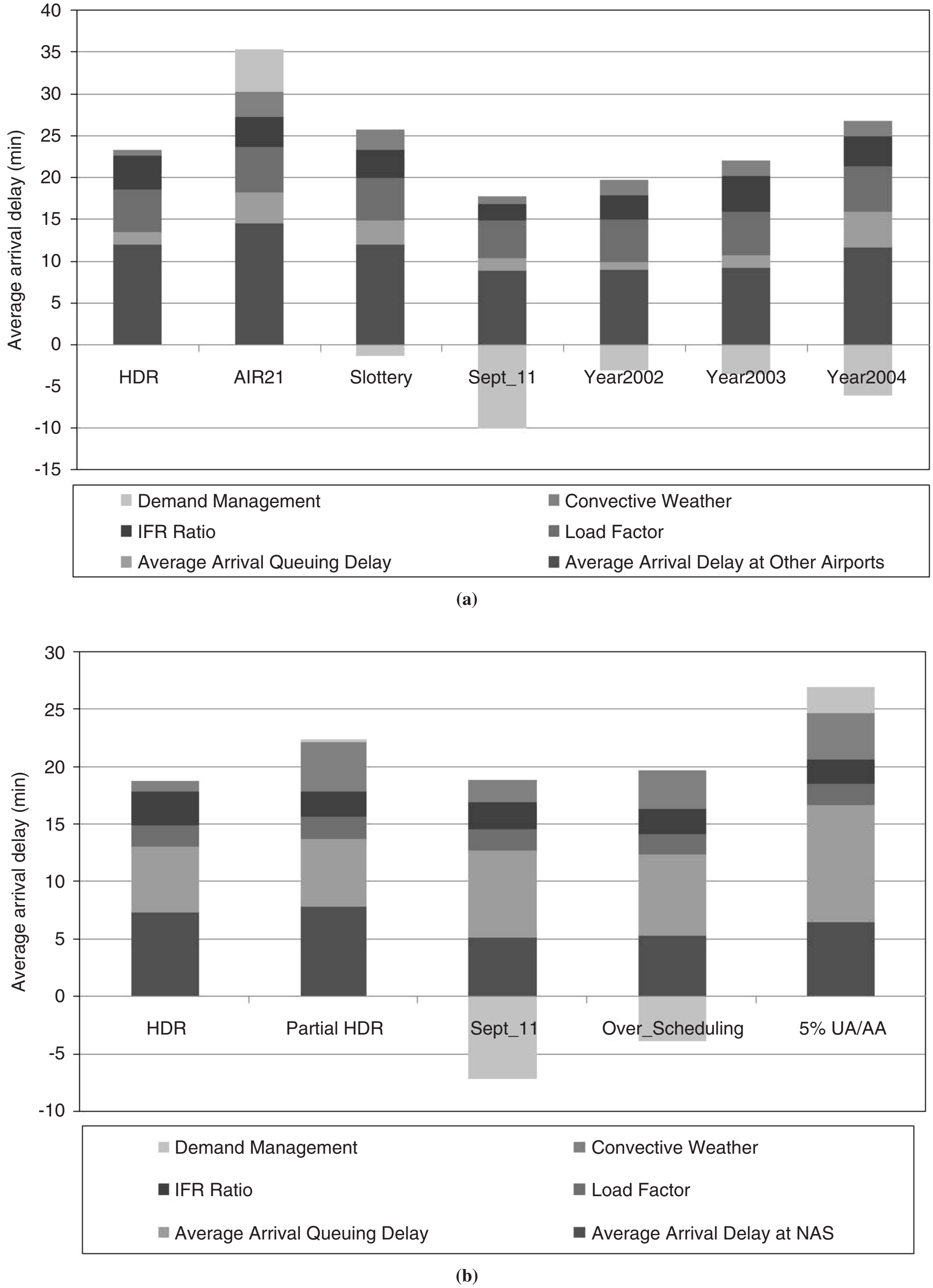
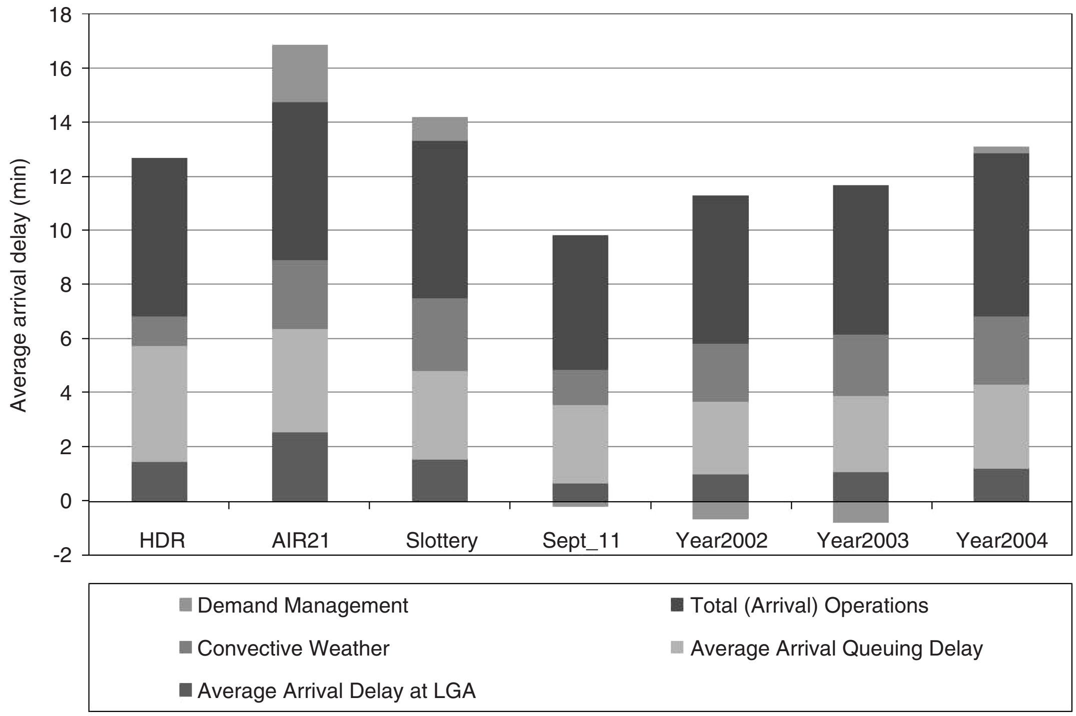


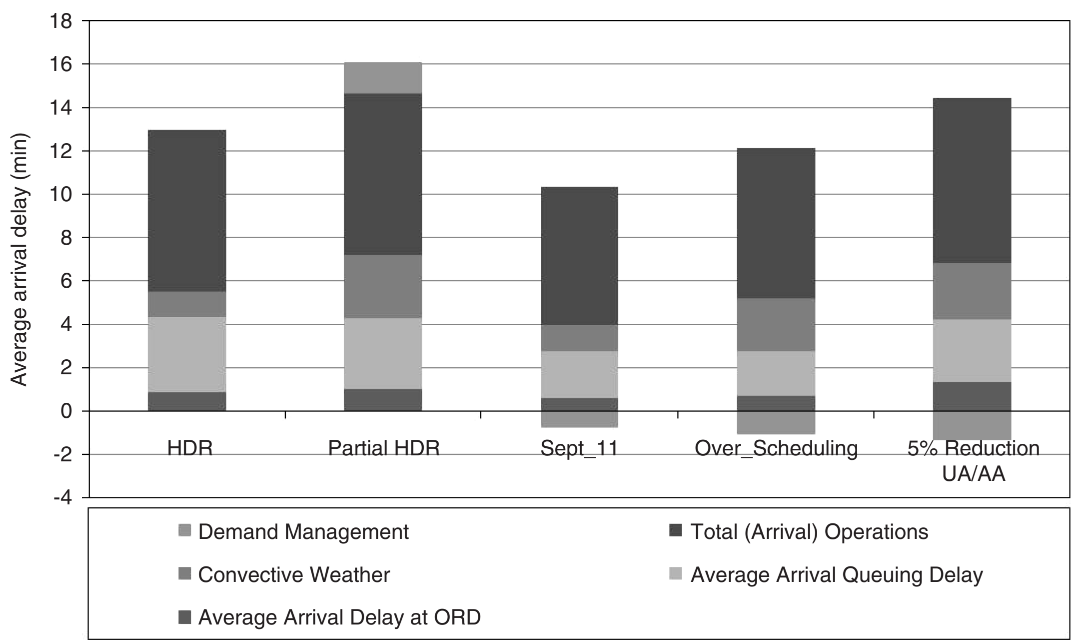
FIGURE 4 Decomposition of LGA and ORD average arrival delay by causal factors and by time period: (*a*) LGA and (*b*) ORD.

of other airports in the NAS and passenger load factors are the major factors affecting average arrival delay at LGA. Average arrival queuing delay and delay in the system are the major contributing factors for the average arrival delay at ORD (Figure 4*b*).

The estimates for the NAS model are shown in Table 2. These are the regression estimates for average arrival delay for flights to 31 benchmark airports other than LGA or ORD. The NAS model for LGA explains a 94.35% variation in average arrival delay, whereas the model for ORD shows a 94.06% variation. The queuing delay, total operations, and thunderstorm ratio are all significant factors affecting arrival delay in the NAS. It is also seen that a 1-min increase in delay at LGA causes a 0.082-min increase in delay in



(a)



(b)

FIGURE 5 Decomposition of NAS average arrival delay considering LGA and ORD by causal factors and by time period: (*a*) LGA and (*b*) ORD.

the NAS, while a 1-min delay at ORD causes a 0.052-min delay in the NAS. Thus, if one considers the ratio of non-LGA to LGA arrivals of about 34 to 1, the effect of a 1-min delay at LGA on non-LGA airports is 34 * 0.082 = 2.788 min. Similarly, if one considers the ratio of non-ORD to ORD arrivals as 15 to 1, the effect on other airports of a 1-min delay at ORD is 15 * 0.052 = 0.78 min. The decomposition of the NAS at LGA (Figure 5*a*) and ORD (Figure 5*b*) produced results similar to those of individual airports. This is an indication that different demand management strategies applied at an individual airport have a definite impact on the whole system. The delay in the NAS due to LGA was more during the AIR-21 period, and the delay due to ORD was more influential during the partial HDR period before sharply increasing in 2004 due to overscheduling.

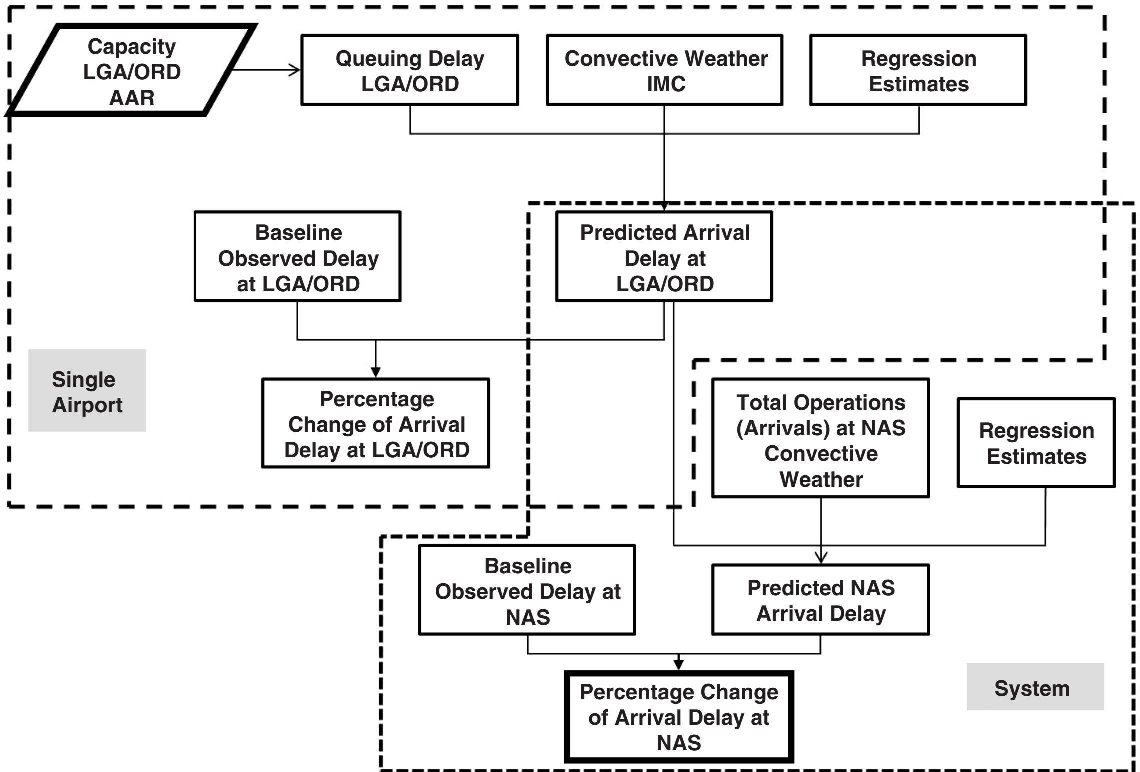


FIGURE 6 Scenario analyses.

SYSTEMWIDE BENEFIT OF CAPACITY EXPANSION OF INDIVIDUAL AIRPORT

It is interesting to note the NAS-wide delay reduction as a result of expansion of a single airport. Given the estimation results of 2SLS equations of LGA and the NAS or of ORD and the NAS, scenario analysis can be conducted to predict the delay reduction under the assumptions of certain percentages of capacity enhancement at each individual airport and no accordingly induced air traffic demand. The entire process was performed in two steps, as shown in Figure 6. The first step produced output in the form of predicted arrival delay for a single airport. This value was compared with baseline observed delay to determine the percentage change of arrival delay at that airport. This predicted delay from the first step along with other variables was then used in the second step to determine the predicted arrival delay in the rest of the NAS. The predicted value could then be compared with baseline delay to determine systemwide improvement. For LGA and ORD, 10%, 20%, and 30% capacity increases were assumed.

The outcomes of this scenario analysis for LGA and ORD are shown in Table 3. The results are noteworthy indicators of the effects of capacity increments on delay reduction. The comparative results show that capacity increase at ORD can yield better outcomes than at LGA in percentage delay reduction. This event can be due to a high congestion rate at ORD, as it was ranked first in the number of total operations until 2004 and was later overtaken by ATL (*10*).

CONCLUSIONS

Airport delay has always been a major problem for the aviation industry. Most previous studies estimated the delay propagated through an individual flight from an airport to the system. This research illustrates the utility of multivariate simultaneous equations to study delay propagation from a single airport to the system, and vice versa. The model developed for LGA and ORD takes into account all the delay causal factors mentioned earlier and also has the scope to include more in the

TABLE 3 Comparison of Scenario Analysis of LGA and ORD Airports

	LGA				ORD			
Capacity	Baseline	10% Increase	20% Increase	30% Increase	Baseline	10% Increase	20% Increase	30% Increase
Airport delay (min)	53.18	52.21	50.56	48.98	18.64	11.48	8.84	7.77
Percent delay reduction at airport	Base	1.83	4.93	7.90	Base	38.48	52.60	58.39
NAS delay (min)	6.44	6.36	6.21	6.06	8.39	8.02	7.89	7.83
Percent delay reduction at NAS	Base	1.36	2.34	2.29	Base	4.40	6.02	6.67

future. The model estimates the effect of each of these factors by means of the 2SLS method. This method is generally used to deal with the bidirectional relationship that exists between dependent variables, in this case, a single airport and the system. The estimated results clearly point toward the existing interdependency between flight delay at an individual airport and the NAS. The delay at LGA and ORD significantly depends on delay at other airports and, similarly, LGA and ORD are major contributors to delay in the system.

The decomposition of delays for different demand management regimes from January 2000 to June 2004 explains the variation in delay throughout the period. The decomposition tries to establish the correlation between various delay causal factors at the airports and their effects on the entire system. For LGA, it shows that maximum delay occurred during the AIR-21 period with slot exemptions. The delay gradually decreased during the slottery regime and reached the lowest point during the post-9/11 period. However, the results to 2004 show that the delay slowly increased to the level of the pre-9/11 slottery period. ORD showed a slightly different variation for delay, with the peak of its delay during 2004. The FAA had to curtail the operations of UA and AA; however, these emptied slots were taken over by other airlines, thus nullifying the efforts of the FAA to reduce delay. The decomposition for the NAS showed results similar to that of individual airports, with total operations in the system being one of the major factors affecting delay.

The research also predicts the systemwide impact of capacity enhancement or improvement in demand management strategies on delay in the NAS. The results indicate that with an increase in capacity there is a proportionate reduction in delay at the airport and the NAS. However, this phenomenon is more dominant at ORD than at LGA. With further observation, it can be seen that the major contributing factor for delay at ORD is queuing delay, while adverse weather is a major problem at LGA. This analysis helps to determine the effectiveness of capacity improvements and can be used as a decision-making tool for airport improvement projects that require massive capital investments in the future.

FUTURE WORK

The research used certain delay-causing factors that were generic; in the future, more airport- or region-specific factors can be used if required. Hence, refining the specifications of multivariate models will help provide more detailed solutions. U.S. airspace system is operated by 22 Air Route Traffic Control Centers, with many airports operating under them. This research methodology can be applied to study the delay propagated from one center to another. Development of a multiequation model is expected in the future to assess whether the delay propagation occurs across all the airports or takes place within a concentrated area. The model can contain a dependent variable that can work as an independent variable in another equation, with their error terms being correlated. These types of models are widely used in economics and business management research studies. The three-stage least-squares model can be used to regress these models and obtain coefficients for multivariate equations.

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The Airfield and Airspace Capacity and Delay Committee peer-reviewed this paper.