MULTI-FACTOR MODEL FOR PREDICTING DELAYS AT U.S. AIRPORTS

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Abstract:

Air transportation is provided by the movement of aircraft through a network of airports. Researchers have established that approximately 84% of delays are generated at airports. These delays propagate to downstream airports where they are absorbed, passed on or enhanced. Researchers have correlated delays with sets of causal factors and have created models to predict aggregate daily delays at airports. Airport Operation Center (AOC) personnel and Traffic Flow Management (TFM) Specialists have suggested that a model for predicting airport delay in 15 minute epochs would have utility.

This paper describes multi-factor models for predicting airport delays in 15 minute epochs at each of the 34 OEP airports. The models are developed using piece-wise linear regressions, using Multi-Adaptive Regression Splines (MARS), for *generated delays* and for *absorbed delays* for each of the 34 OEP airports. The models were generated using historic individual airport data. Accuracy evaluation on separate test data shows mean absolute prediction error of 5.3 minutes for *generated delay* across all the airports, and 2.2 minutes for *absorbed delay* across all the airports. A summary of the factors that drive the performance of each airport is provided. The implications of these results are discussed.

INTROUCUTION

The National Airspace System (NAS) is a large scale transportation network. The nodes of the network are airports that serve to transfer passengers and cargo to other modes of transportation or connect passengers to other flights. The arcs of the network are the procedures and airways of the NAS. A given aircraft originates and terminates flights at airports, traversing through several airports on its flight leg throughput the day. At each airport, an aircraft can accrue a delay or absorb an inbound delay. Figure 1 shows the average inbound delay, generated delay and absorbed delay throughout the day in June, July and August 2005 at Chicago O'Hare International Airport (ORD) and Orlando International airport (MCO). Each bar shows the components of the average wheels-off delay for each flight scheduled to depart in a given 60 minute period. The average delay experienced during this period is the inbound delay (white) plus the generated delay (black) minus the absorbed delay (grey).
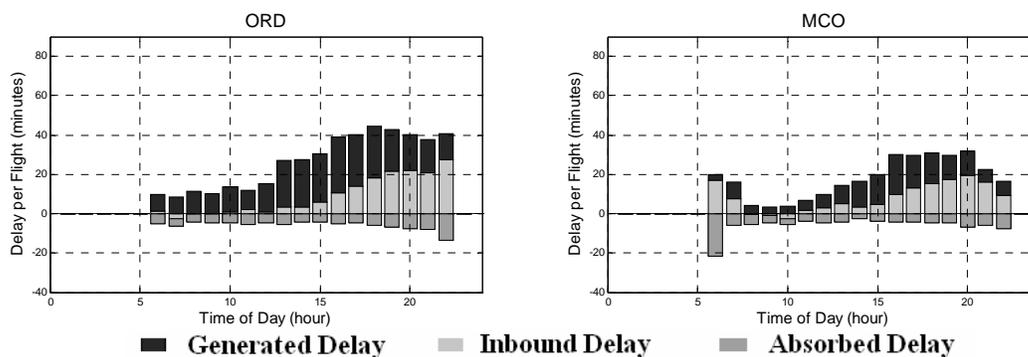

FIGURE 1 Mean value of the components of the delays experienced by flights scheduled to depart in each 60 minute period for 3 summer months. The average delay is the generated delay (black) plus the inbound delay (white) minus the absorbed delay (grey).

Researchers have demonstrated that the majority of flight delays are generated at airports. Using 21-day data in October and November 2001 from Post Operations Evaluation Tool (POET) database, Mueller and Chatterji found that 84% of all delays at ten U.S. airports occurred on the ground (*1*). A more recent analysis using data from the Aviation System Performance Metrics (ASPM) database for June-August 2005 showed that 95% of all delays on flights flying among 34 OEP airports (35 OEP airports exclude HNL) occurred on the ground at the airports. These delays include delays resulting from carrier, congestion, weather, and delays issued for the purpose of Ground Delay Program and other Traffic Flow Management Initiatives.

The relationship between delays and causal factors is highly non-linear (*2*). Delays in the NAS cannot be attributed to single causal factors. Instead they are the result of complex interactions among many factors (*3*). Previous research has established the relationship between environmental factors and aggregated NAS delays (*e.g. 4, 5, and 6*). Other researchers developed aggregated delay models for airports (*e.g. 7*). These models all capture delays as a daily aggregate of delay. Airline Operations Center personnel and TFM Specialists have suggested that models with finer granularity with respect to time would find utility in their operations.

The purpose of this paper is to describe multi-factor models for predicting flight delays *generated* and *absorbed* at individual airports in 15 minute epochs. A piece-wise linear regression model using Multi-Adaptive Regression Splines (*8*) was developed for *generated delays* and for *absorbed delays* for each of the 34 OEP airports analyzed using 3 months of statistical data from the summer of 2005. The results are summarized below:

- The Mean Transformed Absolute Prediction Error (MTAPE) for the *generated delay models* across all the airports is 5.3 minutes. The MTAPE ranged from highest of 9.2 at PHL to lowest of 3.4 at PDX.
- The Mean Transformed Absolute Prediction Error (MTAPE) the *absorbed delay models* across all the airports is 2.2. The MTAPE ranged from highest of 2.7 at BOS and IAD, to lowest of 1.9 at BWI, DFW, LAS, LAX, MDW, MSP, ORD, PDX.

This paper is organized as follows: Section 2 provides a definition of generated and absorbed delay and a summary of previous research in this area. Section 3 describes the methodology used to generated the piece-wise linear models of delay for each airport. Section 4 describes the results of the analysis and the validation of accuracy of the models. Section 5 provides conclusions and a discussion of the implications of these results.

DEFINITION AND PREVIOUS RESEARCH

Generated and Absorbed Delays

In an interconnected, large-scale transportation network such as NAS, airports are nodes, and air corridors are links connecting airports. An aircraft goes through a subset of these nodes and links over a course of day and is affected by these nodes and links sequentially.

The delays that occur at the nodes are defined as airport delays (Figure 2). Aircraft operations at an airport include taxi in, turn-around and taxi out. For the purpose of this study, taxi-in delays are grouped with airborne delays for two reasons: (i) taxi-in delay is small, nearly constant portion of delays, (ii) taxi-in delay is correlated with inter-arrival distances associated with the landing process. Airport delay consists of the aircraft gate arrival time to wheels-off-time.

Positive delay is defined as airport *generated delay* which arises when an aircraft takes more time in any of phases than is scheduled. Negative airport delay is defined as airport *absorbed delay* which arises when an aircraft takes less time in any of phases than is scheduled. In the same manner, the airborne delay is also defined as airborne generated delay if it is positive or airborne absorbed delay is it is negative. Besides airport delays and airborne delays, another critical delay in the NAS network is *inbound delay* to an airport. Inbound delay is an accumulated value of previous leg airport delay and airborne delay. The delay experienced by a flight is the *generated* delay plus the *inbound* delay minus the *absorbed* delay.
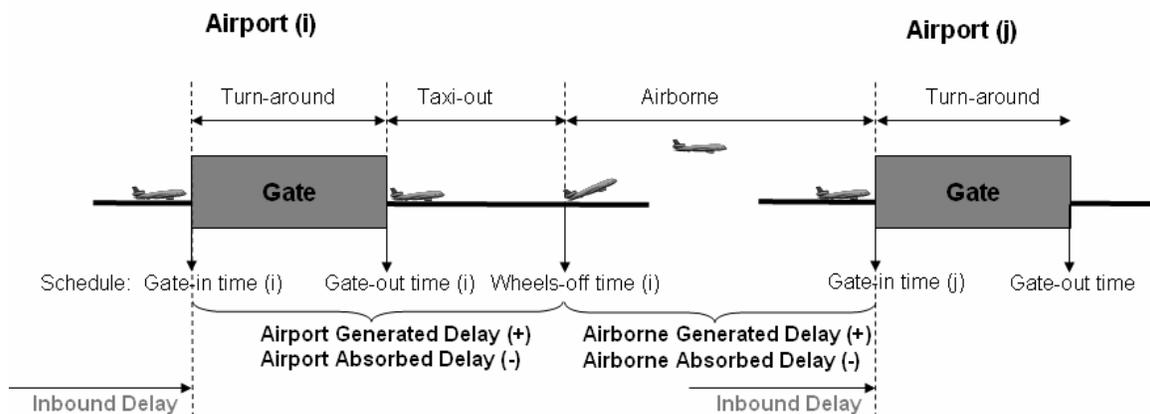

FIGURE 2 Definition of Airport (Airborne) Generated and Absorbed Delay

A significant body of research has been conducted on the analyzing the causes and predicting delays. These studies have identified nine major groups of factors that cause delays:

1. Weather

Weather is a major contributor to large delays. Airport Acceptance Rate (AAR) and Airport Departure Rate (ADR) mostly depends on weather (and on demand as well) (*9*). Airlines usually schedule for fair weather, so any decrease in AAR/ADR caused by weather can lead to delays. Factors related to weather are defined as convective weather, reduced ceiling and visibility, wind and corresponding AAR /ADR at local and destination airport respectively. (*e.g. 7, 10, 11, and 12*) The Quarter Hour Airport Report from FAA database, ASPM, records weather condition of wind, ceiling, visibility, temperature, AAR and ADR for each 15-minute epoch. In addition to ASPM, the categorical weather data of local airport from National Convective Weather Detection (NCWD) is also collected. The states of local weather in NCWD include thunderstorm, heavy-rain, rain, high-wind, wind, low-ceiling, low-visibility and none.

2. Ratio of Operation Demand and Airport Capacity at Scheduled Departure Time

Researchers formulated several kinds of variables to represent the demand, capacity, and the relationship between demand and capacity in NAS. A sample of these variables includes departure demand and queue size (*13*), levels of traffic (*14*), arrival demand and total flight operations (*12*), arrival queue and volume (*11*), airport throughput (*15*), and rho (ρ), the ratio of number of scheduled operations and capacity (*16*). In this research, we separate the scheduled operation into scheduled departure operation and arrival operation, and capacity into departure throughput and arrival throughput. Hence, there are arrival rho (ratio-arr) and departure rho (ratio-dep) in our analysis. We also calculated the scheduled operation demand and throughput at flight's actual departure time. The operations and throughput in 15-minute and 30-minute time window were calculated from ASPM respectively.

For each flight *i*, the departure demand in a 30-minute window is calculated as the total number of aircraft whose scheduled departure time is in the time interval of 15 minutes before the aircraft's scheduled departure time and 15 minutes after its scheduled departure time. For each flight *i*, the departure throughput is calculated as the total number of aircrafts whose actual wheels-off time is in the same time interval. In the situation where the throughput is zero, ratio-dep equals to the departure demand.

3. GDP Holding Time at the Airport for Outbound Flights

A GDP is issued to reduce the volume of inbound flight at a destination airport when the scheduled demand exceeds the airport capacity. Over scheduling and severe weather at destination airport can both initiate a GDP at an origin airport (*7*). An individual flight's GDP holding time measures its assigned Ground Delay Program (GDP) holding time in minutes on the ground by Air Traffic Control before it departs for its destination. Idris et al (*13*) pointed out that the impact from downstream restrictions including the GDP on the aircraft's taxi out time. Hansen and Zhang (*12*) estimated impact of GDP holding time (called EDCT holding in their paper) on the arrival delay at LGA.

4. Scheduled Turn-around Time

Wang et al defined turn around time as the time between an aircraft's arrival and subsequent departure from the same airport. They found ample slack and flight time allowance in turn-around time and flight time can absorb most delays for subsequent flights (*17*). Vigneau referred to scheduled turn-around time as station stop time in his paper and found it is an important variable for flight departure delay (*18*).

5. Carrier Delay

The BTS database lists categories of an air carrier delay ($cdla_i$) , which includes: aircraft cleaning, aircraft damage, awaiting the arrival of connecting passengers or crew, baggage, bird strike, cargo loading, catering, computer, outage--carrier equipment, crew legality (pilot or attendant rest), damage by hazardous goods, engineering inspection, fueling, handling disabled passengers, late crew, lavatory servicing, maintenance, oversales, potable water servicing, removal of unruly passengers, slow boarding or seating, stowing carry-on baggage, weight and balance delays (*19*).

6. Aircraft Substitution (or Rescheduled)

Airlines substitute different aircraft to minimize the impact of long arrival delays (*20*). The criterion to identify a rescheduled (substituted) airframe is set by comparing the airframe's scheduled gate-in time from the previous leg to the scheduled gate-out time at current leg. For an individual flight i, RESCH is an indicator variable. RESCH=1 when scheduled departure time at current leg is earlier than its scheduled arrival time from the previous leg; RESCH=0 otherwise. For each epoch at an airport, *resch* is the proportion of aircraft which were not initially scheduled.

7. En-route Severe Weather Report

Willemain showed in his paper that the airspace of orgin, destination and en-route has a statistically significant impact on delays (*21*). Callaham et al (*3*) developed a Weather Impacted Traffic Index (WITI) to normalize for the potential impact of severe convective weather on en-route performance. The en-route WITI was calculated by overlaying a grid on the U.S. and assigning a weight to each cell based on the potential impact of air traffic performance from the convective weather occurred in that cell. Chatterji and Sridhar (*6*) extended WITI to explain daily delays in the NAS. We use the number of severe weather reports during the scheduled en-route time calculated from NCWD to represent the en-route airspace weather condition. NCWD records the total number of severe weather reports on each flow (*flow*) and airport hourly. If a flight departed at hour *i* and arrived at hour *j,* the total number of severe weather reports is calculated as the summation of portion of $flow_i$,, portion of $flow_j$ and the total number of reports between hour *i+1* and hour *j-1*.

8. In-bound delay

In-bound delay is the delay accumulated from upstream airports and en-route legs. For an aircraft with multiple flight legs, the in-bound delay at any station is the propagated delay from previous legs. Researchers have used this variable to emphasize different aspects of network impact on specific delays. Beatty et. al (*20*) treated inbound delay as the initial delay to identify how it

affects down line delay. Boswell and Evans (*22*) estimated the probability relationship between arrival delay of incoming flight leg and arrival delay of outbound leg in the absence of operational delays on the outbound leg. Vigneau (*18*) estimated the coefficient of arrival delay from the previous leg to the departure delay of the current leg at the same airport. We study how the inbound delay from the previous leg affects the operation delay (airport generated delay and absorbed delay) at the local airport.

9. Scheduled Departure Time

Hsiao and Hansen (*23*) estimated the relationship between time of day and daily NAS delay. Beatty et. al (*20*) also identified the different impact of initial delay at different time of day. In this paper, scheduled departure time is defined in 15-minute epoch from 0 to 95 for a day. We only keep the data where the epoch is between 24 and 87, i.e. 6:00AM to 9:59PM.

Many other factors were also analyzed in various studies. For example, Runway configuration (e.g. *24*), airline (*e.g. 13*), cancellation (*e.g. 25, 26*), aircraft weight (*23*), load factor (*18*) and out-bound leg distance (*27*).

METHODOLOGY

Piece-wise linear regression models, using Multivariate Adaptive Regression Splines (MARS) (*28*), were used to approximate the non-linear relationship between airport delays and their influencing factors. The nonlinearity of a regression model learned by MARS is approximated through a series of continuous piece-wise linear splines. In the space of a predictor variable, there may be separate regression slopes in distinct intervals.

Causal factors of delay included in the original model included those factors identified in the literature and listed in Section 2 above. In situations where there are too many explanatory variables, the collinearity among explanatory variables and model over-specification are major problem in regression analysis. For example, airport weather condition affects airport runway configuration and operation capacity. Weather condition, runway configuration and AAR/ADR are all related to airport delay. Including more predictor variables in the model may reduce estimation bias but increase estimation variance. Including fewer predictor variables may reduce estimation variance but increase bias. MARS's strategy of variable selection is deliberately overfitting a model first then pruning away parts which cause the least increases in sum of squared residuals.

The objective of this research is to identify and estimate the causal factors influencing airport delay. Pearl's criterion for causal attribution is: *Variable R is said to have a causal influence on variable D if a directed path from R to D exists in every minimal structure consistent with the data* (*29*). Based on this theory, an approach was developed to find a minimum size of regression in order to identify a more general relationship regarding to airport delays across 34 OEP airports. The criteria to decide a minimum size model is based on the distribution of prediction errors rather than the summation of squared prediction errors.

The historical data from each of the 34 OEP airports was separated into three sets: training data for creating the model, testing data set #1 for selecting the factors in the minimum size model, and testing data set #2 for validation. The data from June and July 2005 was treated as training data. The data from the first 15 days in August 2005 was treated as testing data set #1. The last 15 days (excluding the 31st) in August 2005 was reserved for testing data set #2. For each response

variable – generated or absorbed dealy at one of 34 OEP airports –a set of predictor variables was selected and a model was generated according to the following steps:

1. Begin with all independent variables, using MARS to build a full-size regression model from training data for each airport. The selected variables in the full-size model have variable importance greater than 0. If necessary, transform variables to obtain randomly distributed residuals. A square root transformation was applied to both airport generated delay and absorbed delay. Calculate residuals on training data. $R_{full} = y_{train(i)} - \hat{y}_{train(i)}$ where, $y_{train(i)}$ is the true delay value of case i in training sample, $\hat{y}_{train(i)}$ is the estimated delay value of case i calculated from the full-size model.

2. Apply full-size model on testing data set #1 to obtain prediction error $E_{full} = y_{test(i)} - \hat{y}_{test(i)}$ where, $y_{test(i)}$ is the true delay value of case i in testing sample, and $\hat{y}_{test(i)}$ is the estimated delay value of case i calculated from the full-size model.

3. Create a list of the selected variables from all 34 OEP airports, Count the number of times each variable appears among the 34 airports. The maximum appearance count is 34.

4. Build a baseline reduced-size MARS model using variables whose appearance count is equal to 34. Calculate residuals R_{reduce} for the reduced-size model for each airport.

5. Apply reduced-size model on testing data and get prediction error E_{reduce}.

6. Conduct two-sample t tests to test the hypothesis that the residuals from the regression and the prediction errors from the full and reduced size models have equal means. Conduct Kolmogorov-Smirnov tests to test the hypothesis that the residuals from the regression and the prediction errors from the full and reduced size models have the same distribution.

7. For each airport, accept the reduced-size model as the minimum-size model if the residuals from the training sample and the prediction errors from the testing sample pass both the t test and the Kolmogorov-Smirnov test at level 0.05, i.e., the hypotheses of equal sample mean and same distribution were not rejected.

8. For each airport for which no model has yet been accepted, select the variable with the highest variable importance as calculated for the in full-size model, from among the variables not yet considered for addition to the model. Add the variable to the model if one of the following conditions is met: (1) adding the variable reduces the magnitude of the mean prediction error; or (2) the distribution of the residuals and prediction errors changes when the variable is added.

9. Continue Steps 7 and 8 till both tests are not rejected.

10. The independent variables in minimum-size model are the directed factors for delays at corresponding airports.

RESULTS

The models for generated and absorbed delay are described below, followed by an analysis of the causal delay factors for each airport, and an assessment of the accuracy of the model for each airport.

Multi-factor Models for Generated and Absorbed Delay

The general form of the equation for *generated* and *absorbed delay* is illustrated in the example below for ORD. The response variable, airport *generated delay*, is transformed by taking the

square root to stabilize the variance of residuals. The same transformation was done on airport *absorbed delay* also. The pair $0.051*\max(0, x_1 - 1)$ and $0.404*\max(0, 1 - x_1)$ indicates two different slopes at two segments of carrier delay value space. Note also there are several interaction terms in the model. For example, the pair $-0.014*\max(0, 86 - x_3)*\max(0, 1 - x_1)$ and $-1.011*\max(0, x_3 - 86)*\max(0, 1 - x_1)$ explains the different joint impact of carrier delay and scheduled departure time if the scheduled departure time is before or after 86 epoch (9:30PM).

$$
\begin{aligned}
\sqrt{generatedDelay} = {}& 3.924 \\
& + 0.051*\max(\,0, x_1 - 1\,) \\
& + 0.404*\max(\,0, 1 - x_1\,) \\
& + 0.056*\max(\,0, x_2 - 5.7\,) \\
& - 0.028*\max(\,0, 5.7 - x_2\,) \\
& - 0.012*\max(\,0, 63 - x_3\,) \\
& + 0.686*\max(\,0, x_4 - 0.23\,) \\
& + .348120E\text{-}03*\max(\,0, x_5 - 92.154\,)*\max(\,0, x_4 - 0.23\,) \\
& + 5.331*\max(\,0, x_6 - .696272E\text{-}09\,) \\
& + 0.004*\max(\,0, x_1 - 4.750\,)*\max(\,0, 5.7 - x_2\,) \\
& - 0.035*\max(\,0, 4.750 - x_1\,)*\max(\,0, 5.7 - x_2\,) \\
& - .188081E\text{-}04*\max(\,0, x_5 - 1595.625\,)*\max(\,0, x_3 - 63\,) \\
& + .509046E\text{-}05*\max(\,0, 1595.625 - x_5\,)*\max(\,0, x_3 - 63\,) \\
& - 1.011*\max(\,0, x_3 - 86\,)*\max(\,0, 1 - x_1\,) \\
& - 0.014*\max(\,0, 86 - x_3\,)*\max(\,0, 1 - x_1\,) \\
& - 0.054*\max(\,0, x_3 - 73\,)*\max(\,0, x_4 - 0.23\,) \\
& - 0.014*\max(\,0, 73 - x_3\,)*\max(\,0, x_4 - 0.23\,)
\end{aligned}
$$

where, x_1 – carrier delay

x_2 – GDP holding time

x_3 – scheduled departure time

x_4 – ratio of departure demand and throughput

x_5 – en route weather report

x_6 – reschedule

Factors Causing Delay

The factors that appeared in the models for *airport generated delay* are listed in Table 1. GDP Time and Carrier delay appear in the models for all airports. Inbound delay is a significant factor in the model for 26 of the 34 airports. En-route weather and several other factors appear in models for a few of the airports.

TABLE 1 Selected Factors Used in Equations for Generated Delay at Each Airport

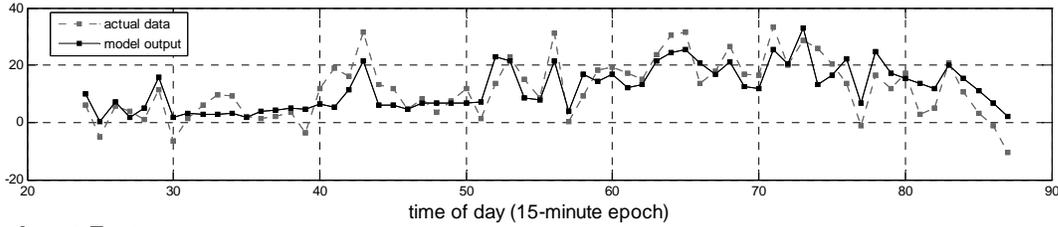|	GDP time	Carrier Delay	Inbound Delay	Departure Demand /Capacity (30 mins)	Re-schedule	Dep-time	Weather	En-Route Weather	Arrival Demand/ Capacity (30 mins)	Departure Demand /Capacity (15 mins)	AAR	Outbound Leg Distance
BWI	x	x	x	x	x							
PIT	x	x	x	x	x			x				
SFO	x	x	x	x	x	x						
DFW	x	x	x	x		x	x					
DTW	x	x	x	x		x						
FLL	x	x	x	x		x						
MIA	x	x	x	x		x						
CLE	x	x	x	x		x						
CVG	x	x	x	x		x						
TPA	x	x	x	x		x						
DCA	x	x	x	x					x			
MSP	x	x	x	x								
SAN	x	x	x	x								
MEM	x	x	x					x		x		
IAD	x	x	x		x	x						
LAS	x	x	x		x	x						
MCO	x	x	x		x	x	x					
BOS	x	x	x									
CLT	x	x	x					x				
LAX	x	x	x									
MDW	x	x	x									
PDX	x	x	x									
SEA	x	x	x									
SLC	x	x	x									x
STL	x	x	x									
DEN	x	x		x	x							
PHX	x	x		x	x						x	
ORD	x	x		x	x	x			x			
PHL	x	x		x		x			x			
EWR	x	x		x		x						
IAH	x	x		x		x						
LGA	x	x		x					x	x		
ATL	x	x			x							
JFK	x	x				x						

The factors that appeared in the model for of airport *absorbed delay* at all 34 OEP airports are inbound delay, scheduled turn-around time and carrier delay. Seven airports (CLE, DCA, EWR, MEM, MIA, PIT and TPA) have GDP holding time and 2 airports (LAS and TPA) have scheduled departure time as additional factors.

Validation with Test Data

To validate the estimation power of the minimum size model, we choose the data from the last 15 days (excluding 31st) of August 2005. The results for all the models for all the airports are summarized in Table 2.

Figure 3 shows the estimated airport delay for ORD on 24 August, 2005. The solid line in the top chart represents the estimated airport delay for each 15 minute interval given the values of the factors shown in the charts at bottom of the figure. The dashed line in the top chart is the actual delay data for each 15 minute epoch. The airport delay is the summation of airport generated delay and absorbed delay for each epoch. The absolute value of errors is less than 15 minutes.
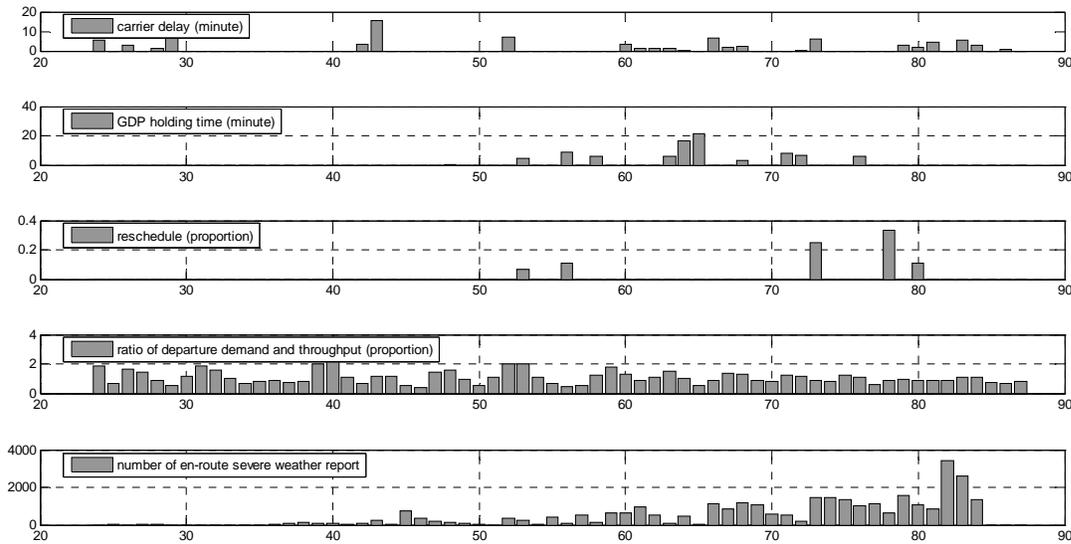

FIGURE 3 Comparison of Actual Data and Model Output on August 24 2005 at ORD

Several measures of the overall estimation performance of the models for *generated* and *absorbed delay* are computed on the August data. The Mean Square Prediction Error (MSPE) is obtained by subtracting the transformed data (square root of delay) from the model prediction, squaring the result, and summing over all data values. We also transformed the model prediction back to the original scale, subtracted from the actual delay, and summed to obtain the Mean Transformed Prediction Error (MTPE). Finally, the Mean Transformed Absolute Prediction Error (MTAPE) is obtained by summing the absolute prediction errors for delays. Because there are both negative and positive errors, the MTAPE, estimates the variability in delay predictions.

$$MSPE = \frac{1}{m}\left(\sum\left(\text{estimation} - \sqrt{\text{actual Data}}\right)^2\right)$$

$$MTPE = \frac{1}{m}\left(\sum\left(\text{estimation}^2 - \text{actual Data}\right)\right)$$

$$MTAPE = \frac{1}{m}\left(\sum\left|\text{estimation}^2 - \text{actual Data}\right|\right)$$

where, *m* is number of records in testing data set 2

From Table 2, neither MSPE nor MTPE is far from zero. For *generated delay*, the MSPE ranges between 0.8 and 2.5minutes. The MTPE ranges between -3.4 and 1.6 minutes. For *absorbed delay*, the MSPE ranges between 0.5 and 1.2 minutes, and the MTPE ranges between 0.3 and 1.7 minutes. All mean absolute prediction errors from testing samples at 34 OEP airports are between 3.4 and 9.2 minutes for *generated delay*, and between 1.9 and 2.7 minutes for *absorbed delay*. The average value of MTAPE for airport *generated delay* is 3.4 minutes; the average value of MTAPE for airport *absorbed delay* is 1.9 minutes.

TABLE 2 Validation Result of Airport Generated Delay at 34 OEP Airports

	Airport Generated Delay Model			Airport Absorbed Delay Model		
	MSPE	MTPE (minute)	MTAPE (minute)	MSPE	MTPE (minute)	MTAPE (minute)
ATL	1.3	-2.1	6.5	0.6	0.9	2.3
BOS	1.3	-1.1	5.4	0.8	1.7	2.7
BWI	1.4	-0.2	4.8	0.7	1.1	1.9
CLE	1.9	-1.8	4.9	0.7	1	2.4
CLT	1.8	-1.5	5.9	0.7	1.4	2.3
CVG	1.3	-1.3	4.8	0.8	1.2	2.4
DCA	1.1	0.2	3.8	0.5	1.3	2.1
DEN	1.2	-0.3	4	0.5	1.1	2
DFW	1.2	-1.5	5.3	0.5	1	1.9
DTW	1.1	0.5	5.2	0.8	1.1	2.6
EWR	1.5	0.5	7.8	0.8	1.3	2.6
FLL	1.9	-0.1	5.4	0.9	0.6	2.4
IAD	2.2	1.4	7	0.8	1.7	2.7
IAH	2.5	-3.4	7.9	0.7	1.3	2.2
JFK	1.7	-0.1	7.9	0.8	1.3	2.5
LAS	1	0.1	4	0.6	0.8	1.9
LAX	0.8	-0.3	3.5	0.5	0.6	1.9
LGA	1.7	-2.1	7.5	0.7	1	2.3
MCO	1.3	-0.8	4.5	0.6	0.9	2.1
MDW	1.5	0.7	4.5	0.6	1	1.9
MEM	1.7	-0.5	5.9	1.2	1.3	2.5
MIA	2.2	-0.7	6.1	0.8	0.8	2.2
MSP	1.4	1.5	6.3	0.8	0.3	2.4
ORD	1	1.6	5.7	0.5	1.1	1.9
PDX	1.3	-1.6	3.4	0.7	0.7	2.1
PHL	2.1	1.3	9.2	0.7	1.1	1.9
PHX	1.2	-0.9	4.8	0.7	0.6	2.2
PIT	1.5	-1	4.1	0.8	1.4	2.5
SAN	1.6	-1.9	4.6	0.7	1	2.3
SEA	0.9	-0.7	3.7	0.7	1	2.2
SFO	1.5	-0.3	4.6	0.6	1	2.5
SLC	1.4	-1.7	4.4	0.6	0.9	2
STL	1.3	-0.5	3.9	0.8	1.4	2.3
TPA	1.6	-1	4.5	0.6	1.2	2.1
Average	**1.5**	**-0.6**	**5.3**	**0.7**	**1.1**	**2.2**
Min	**0.8**	**-3.4**	**3.4**	**0.5**	**0.3**	**1.9**
Max	**2.5**	**1.6**	**9.2**	**1.2**	**1.7**	**2.7**

CONCLUSION

Piece-wise linear regression models, using Multi-Adaptive Regression Splines (Friedman 1991), were developed for *generated delays* and for *absorbed delays* for each of the 34 OEP airports using 3 months of statistical data from the summer of 2005. The accuracy of the models on a separate set of test data is summarized below:

- The Mean Transformed Absolute Prediction Error (MTAPE) for the *generated delay models*, averaged across all 34 OEP airports, is 5.3 minutes. The MTAPE ranged from a high of 9.2 at PHL to a low of 3.4 at PDX.
- The Mean Transformed Absolute Prediction Error (MTAPE) for the *absorbed delay models*, averaged across all 34 OEP airports, is 2.2. The MTAPE ranged from a high of 2.7 at BOS and IAD, to a low of 1.9 at BWI, DFW, LAS, LAX, MDW, MSP, ORD, and PDX.

These models could be applied by AOC and TFM personnel using a tool, as illustrated in Figure 4. Such a tool would enable a user to perform "what if" analysis by making changes in causal factors at various times of the day and observing the predicted effects. The display would include multiple delay predictions to better understand the impact of one or more types of delays.
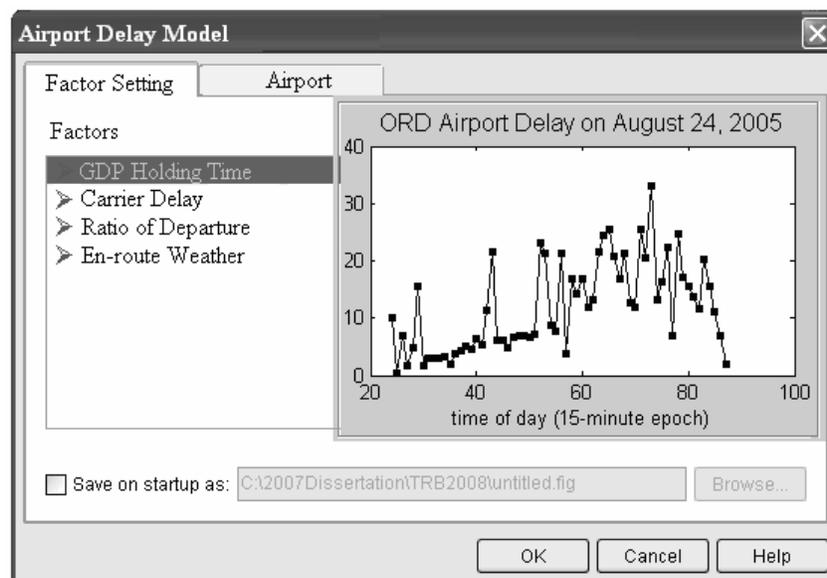

FIGURE 4 GUI for Multi-factor Model for Predicting Airport Delays in 15 Minute Epoch

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