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ANALYSIS OF AIRCRAFT ARRIVAL AND DEPARTURE DELAY CHARACTERISTICS

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Abstract

The increase in delays in the National Airspace System (NAS) has been the subject of several studies in recent years. These reports contain delay statistics over the entire NAS, along with some data specific to individual airports, however, a comprehensive characterization and comparison of the delay distributions is absent. Historical delay data for these airports are summarized. The various causal factors related to aircraft, airline operations, change of procedures and traffic volume are also discussed. Motivated by the desire to improve the accuracy of demand prediction in enroute sectors and at airports through probabilistic delay forecasting, this paper analyzes departure and arrival data for ten major airports in the United States that experience large volumes of traffic and significant delays. To enable such an analysis, several data fields for every aircraft departing from or arriving at these ten airports in a 21-day period were extracted from the Post Operations Evaluation Tool (POET) database. Distributions that show the probability of a certain delay time for a given aircraft were created. These delay-time probability density functions were modeled using Normal and Poisson distributions with the mean and standard deviations derived from the raw data. The models were then improved by adjusting the mean and standard deviation values via a least squares method designed to minimize the fit error between the raw distribution and the model. It is shown that departure delay is better modeled using a Poisson distribution, while the enroute and arrival delays fit the Normal distribution better. Finally, correlation between the number of departures, number of arrivals and departure delays is examined from a time-series modeling perspective.

1. Introduction

An application of the Enhanced Traffic Management System (ETMS) is to provide an estimate of traffic demand at sectors and airports. The demand is computed based on airline schedule data, historical traffic data, filed flight plans, and radar track data[1]. Host computer systems at the various Air Route Traffic Control Centers (ARTCC's) provide flight plan and radar derived time-stamped track positions to the ETMS. These data are used with flight plan-based trajectory models to predict the locations of both airborne aircraft and aircraft that are scheduled to depart. The forecast positions are used to project demand at airports, sectors, and fixes. For aircraft that are scheduled to depart in the future, departure time uncertainty is the major cause of demand prediction error; therefore increased departure time accuracy will directly increase the accuracy of such predictions. This study is motivated by the desire to improve the forecasting accuracy of departure times with a probabilistic delay time model.

Since traffic management decisions are influenced by the predicted demand, better demand forecasting is desirable. There have been attempts to improve forecasting by using alternative trajectory prediction methods in systems that are currently being developed such as the FAA/CAASD Collaborative Routing Coordination Tools (CRCT) program, NASA Future ATM Concepts Evaluation Tool (FACET), and the NASA/FAA Center TRACON Automation System (CTAS) based Traffic Flow Automation System (TFAS).[2-4] Masalonis, et. al.,[5] summarizes the results of preliminary analysis of CRCT traffic prediction performance compared to the ETMS. The study reveals improvements in demand forecasting are possible over ETMS by modeling airspace restrictions. However, the predictability varies according to factors such as the type of sector and time horizon, irrespective of the trajectory prediction engine used. Similar trends have also been reported in preliminary studies using TFAS and FACET trajectory prediction methods.[4,6,7] Clayton and Murphy[4,6] show TFAS is better able to predict the trajectories of arrival traffic than ETMS as it uses a detailed adaptation near the airport, has improved modeling of restrictions at the meter fixes, and uses a four-dimensional trajectory prediction algorithm. A slight improvement is also seen for departure traffic. Compared to the prediction accuracy of active flights, the prediction accuracy of proposed flights was found to be poor due to the departure time uncertainty of proposed flights.

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From a search of the literature,[4-7] one may conclude that to characterize the uncertainty of traffic demand forecasts, departure uncertainty must be modeled. Meyn[8] describes a probabilistic method for air traffic demand forecasting using a probability distribution of an aircraft's location about a nominal location or as a distribution in time about a reference time (i.e. the sector boundary crossing time). The stochastic approach may be beneficial even if early and accurate intent information is provided because of the likelihood that unanticipated events may prevent departure at the intended time. Such events include unscheduled maintenance, baggage handling problems and passenger loading issues, and often cause delay in departure from the gate.

The objective of this paper is to analyze departure and arrival data for ten major airports in the United States and characterize the delay distributions for traffic forecasting algorithms. Global delay statistics for the entire National Airspace System (NAS) and for major airports in the U.S., reported by the various studies, are discussed in Section 2. Collection of airport arrival and departure data is described in Section 3, and delay metrics are formulated in Section 4. The numerical values of these metrics are also provided here in tabular form. Additionally, the aggregate trends are examined as a function of the days of the week. Section 4 describes modeling of departure, enroute and arrival delays using Normal and Poisson distributions. Finally, the conclusions are provided in Section 5.

2. Delay Statistics

Causes of delays in the NAS have been the subject of several studies in recent years.[9-12] These reports contain delay statistics over the entire NAS along with some data specific to individual airports. They do not provide a comprehensive breakdown and analysis of the arrival, departure, and enroute delays for aircraft operations from major airports. This section will define the different regimes in which delays occur, give basic statistics on their magnitudes and frequencies, and offer some explanations as to why they arise.

There is no industry-wide standard definition or measure of delay. Each organization involved in this area tailors the definition to suit the purpose at hand, however there are standard and precisely-defined events that can be used for this purpose: Out, Off, On, and In (OOOI) times. *Out* time refers to the time of pushback (specifically when the parking brake is released). *Off* time refers to the takeoff time at which weight is no longer borne on the landing gear. *On* time is associated with the touchdown time, and the *In* time is related to the moment the parking brake is applied at the gate. These times are recorded and reported by the respective airline, and their definitions will be used for delay and transit time computations in this paper.

The Federal Aviation Administration (FAA) categorizes delays into gate delay, taxi-out delay, enroute (in flight) delay, terminal delay and taxi-in delay. Each category of delay arises when the aircraft requires more time in that regime than was scheduled. For example, terminal delays result when aircraft are held in holding patterns close to the airport prior to landing. Due to business reasons, air carriers interpret these delay definitions somewhat differently. For instance, some air carriers report arrival at the gate when the parking brake is applied, while others use the opening of the passenger door as the gate arrival event. Although the time difference between these events is small, it can nevertheless be the deciding factor in whether a flight is recorded as on time or delayed.

Two government agencies keep air traffic delay statistics in the United States. The Bureau of Transportation Statistics (BTS) compiles delay data for the benefit of passengers. They define a delayed flight as one in which the aircraft fails to release its parking brake less than 15 minutes after the scheduled departure time. The FAA is more interested in delays indicating surface movement inefficiencies and will record a delay when an aircraft requires 15 minutes or longer over the standard taxi-out or taxi-in time (*Out* to *Off* time, or *On* to *In* time, respectively).

In order to understand historical delay data, such as those maintained by the BTS and the FAA, it is useful to consider the phenomenon of scheduled delay. As congestion in the NAS increased in the 1990's, airlines recognized the value of minimizing the incidence of delays as recorded and reported to the public. The simplest way of reducing delays was not to increase the speed and efficiency of the system to meet the scheduled time, but to push back the scheduled time to absorb the system delays. As a result, one estimate put the number of scheduled delays that were built into airline schedules in 1999 at 22.5 million minutes.[13] The number of arrival delays reported by BTS would have been nearly 25% higher in 1999 if airlines had maintained their 1988 schedules.

An audit report by the Department of Transportation (DOT) states that the FAA reported an average departure delay time increase from 41.1 minutes in 1998 to 43.5 minutes in 1999.[13] During the same period, the BTS reported a similar rise from 49.3 to 50.5 minutes. The difference in reported delay times are due to the alternative ways, defined above, in which the FAA and the BTS track delays. Average delay times for ten major U.S. airports, which are listed in Table 1, are summarized in Table 2. The delay times reported in Table 2 include departure, enroute and arrival delays.

Table 3 shows the average percentage of delayed aircraft for each of the ten airports in Table 1, broken down by departures and arrivals, for the twelve months ending in October 2001.[14] From Table 3, it is evident that the percentages of delayed departures and arrivals are similar in some cases, suggesting that delay is frequently incurred on departure and carries through to arrival. The percentage of delayed departures or arrivals in 2001 was lower than in 2000, which was a record year for all types of delays compared to the previous level set in 1990.[15]

The top ten airports with the most arrival delays in 2000, as defined by the inspector general, saw an increase of 24.2% since 1999.[16] The FAA reported that over the entire NAS in 2000, 27.5% of all aircraft were delayed, canceled, or diverted.[16]

In summary, air traffic delays have been on a steady rise since the 1990s. A statement by the DOT[16] notes that according to BTS, the number of delayed aircraft has increased by 30% between 1995 and 2000. The report also shows that using FAA statistics, the delays increased by 90% during the same period, and flight cancellations soared 104 percent. The annual cost of delays in 1999 was just over 3.2 billion dollars. This compares to roughly 7.85 billion dollars in net profit for all airlines, representing a 27% drain on financial resources.[13]

Table 1. Major U. S. airports used in study.

ATL	Atlanta
BOS	Boston
DFW	Dallas/Fort Worth
EWR	Newark
JFK	New York - John F. Kennedy
LAX	Los Angeles
LGA	New York – La Guardia
ORD	Chicago O'Hare
SFO	San Francisco
STL	St. Louis

Table 2. Average duration of BTS-reported delay times in minutes by airport and year.[13]

Airport	1995	1999
ATL	28.87	37.67
BOS	42.84	43.96
DFW	34.18	38.70
EWR	45.73	49.98
JFK	37.98	36.44
LAX	36.10	37.79
LGA	31.32	39.95
ORD	47.30	55.83
SFO	35.62	52.96
STL	38.39	48.12

Table 3. Percentage of delayed aircraft with respect to total aircraft, Nov 00 to Oct 01.[14]

Airport	Departures	Arrivals
ATL	13.7	8.6
BOS	20.0	13.4
DFW	21.1	17.1
EWR	9.9	10.3
JFK	24.3	16.5
LAX	14.7	16.0
LGA	13.6	12.5
ORD	19.3	19.2
SFO	18.9	25.0
STL	14.5	14.5

Studies have identified the stages of flight in which delays occur and the causal factors that result in delays. For example, the DOT[16] classifies delays as gate delay, taxi-out delay, airborne delay and taxi-in delay. Figure 1 shows their contribution to the total delay. Observe from the figure that 84% of all delays occur on the ground (gate, taxi-out, taxi-in), out of which 76% are prior to takeoff (gate, taxi-out), suggesting that focusing on ground delay prediction will have the most impact on improving forecasting algorithms.[16] Surface movement inefficiencies are not the only reason for delays on the ground. Ground delay programs, enroute capacity constraints, aircraft maintenance issues, ground services (fuel, baggage and catering), customer service issues, late aircraft/crew arrival, and poor weather conditions elsewhere all contribute to surface

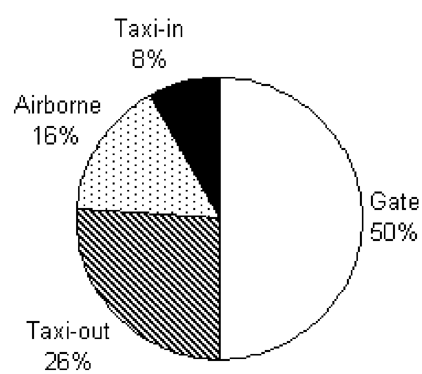

Fig. 1 Distribution of delays by phase of flight.[16]

delays.[16] The impact of the most common and important of these factors will be discussed.

Weather is the main contributor to delays in the air traffic control (ATC) system as shown in Fig. 2. Traffic volume delays are caused by an arrival/departure demand that exceeds the nominal airport arrival rate (AAR)/airport departure rate (ADR). The demand may also exceed the airport capacity if AAR and ADR are reduced due to weather conditions at the airport, equipment failure or runway closure. ATC equipment outages are also responsible for a small number of delays.

In addition to the above-listed causal factors for delays, introduction of new equipment and operational procedures have been known to contribute to the delays. For example, Fig. 3 shows that introduction of the Display System Replacement (DSR) program, which is designed to upgrade controller's displays, caused 21% of the increase in delay in 1999 since it required the controllers to learn a new system.

Restrictions on Land And Hold Short Operations (LAHSO), a change of procedure, also contributed to an increase in delay. LAHSO is designed to permit simultaneous use of intersecting runways. The landing aircraft is instructed to stop just before the intersecting runway so that another aircraft may use it at the same time. To ensure safe operations, the FAA added restrictions to this policy in 1999, which effectively reduced the capacity of many large airports and increased delay in the NAS.[13]

Delays may also be attributed to airline operations procedures.[13] The first contributing factor is the organization of operations into a hub and spoke system by the airlines. The hub-spoke operations cause banks of aircraft to arrive together and then depart together. This type of operation is desirable from an airline point of view because it allows the passengers, aircraft and crew to be rerouted to various destinations. They also provide airlines the opportunity to consolidate passengers into some flights while canceling others. The main drawback of this procedure is that the airport experiences arrival and departure rushes with little resource utilization in the interim periods. The second factor is increased use of regional jets instead of turboprops. The turboprops required a smaller runway, climbed more slowly and flew at lower altitudes than the jets. These characteristics allowed them to be naturally separated from the higher altitude jet traffic. Increased numbers of smaller jets, which operate in the same flight regime as the larger jets, means more aircraft competing for the same airspace, thereby increasing congestion and delays.

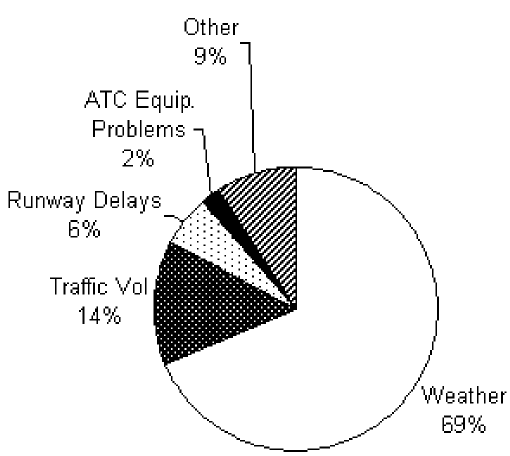

Fig. 2 Distribution of arrival and departure delay causes in 2000.[15]

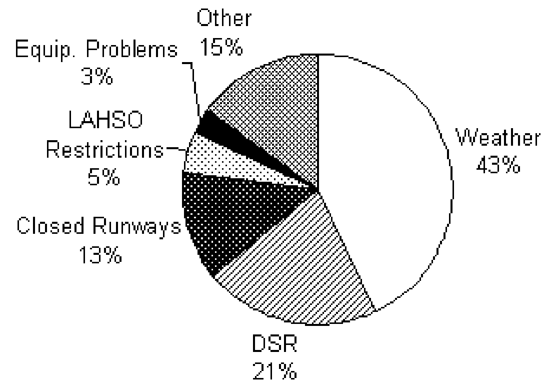

Fig. 3 Distribution of reasons for increases in delay in 1999.[13]

3. Data Collection

Ten major U. S. airports that experience significant delays were selected for the study of departure, enroute and arrival delays. These major hub airports, listed in Table 1, are responsible for a significant portion of the traffic in the NAS and they also bear the burden of a large portion of the delays.

The data needed for the analysis of delays for these airports were extracted using the Post Operations Evaluation Tool (POET) for the three-week period spanning October 14, 2001 to November 3, 2001. The three-week duration was chosen to have enough data for statistically meaningful results and to make possible analysis of the data as a function of days of the week.

POET is an analysis system developed under the FAA's Collaborative Decision Making (CDM) program. Since it is built on top of a relational database, users can easily query, filter, and visualize the flight information contained in the ETMS data archive using a variety of interactive charts and tables. Analysis results can be aggregated by departure and arrival airports, filed arrival fixes, departure and arrival times, National Route Program (NRP)/non-NRP status, departure and arrival centers, and by the class of the user, among other functionalities. The POET server installed at the Air Traffic Control System Command Center (ATCSCC) archives a rolling 45-day set of ETMS data.[17]

The following data fields were extracted for each aircraft in the POET database:

- identification code,
- date of departure,
- airport code,
- scheduled time of departure,
- actual time of departure,
- scheduled flight time,
- actual flight time,
- scheduled time of arrival, and
- actual time of arrival.

It should be noted that the scheduled time of departure in the POET database is an *Out* time filed by the airline approximately 30 to 120 minutes before departure, plus an estimated taxi time. The actual time of departure in the database is the *Off* time, which is the time the aircraft lifts off the runway. The difference between the two is used as a measure of delay for the forecasting process. A bias correction for the difference between the actual and scheduled times can always be applied to improve the accuracy of the schedule-based prediction method.

4. Results

The data extracted from POET were analyzed to generate: tables that list the values of the delay metrics, described below, for the chosen ten airports for the 21 day period; bar charts that describe various attributes of traffic as a function of days of the week; and models of departure delay, enroute delay and arrival delay distributions.

Delay Statistics of Major Airports

The delay metrics were generated for a typical day by first averaging for a day of operations and then averaging the result over the 21 days. The average number of operations for any day is determined as:

$$f_1 = \frac{\sum_{1 \le i \le m} n_i}{m} \tag{1}$$

where n_i is the number of departures or arrivals on the i^{th} day and m is the number of days.

The average delay for a day of operations at a particular airport is:

$$\Delta_i = \frac{\sum_{1 \le j \le n_i} \delta_{j,i}}{n_i} \tag{2}$$

with delay defined as:

$$\delta_{j,i} = (t_a - t_s)_{j,i} \tag{3}$$

Here, n_i is the number of departures or arrivals on the i^{th} day, t_s is the scheduled departure and t_a is the actual departure time of the j^{th} aircraft on the i^{th} day. The average over the m number of days can now be computed as:

$$f_2 = \frac{\sum_{1 \le i \le m} \Delta_i}{m} \tag{4}$$

f_2 is an average delay over the number of aircraft and the number of days at a specific airport.

A third measure, f_3, is the percentage of aircraft departing late and is defined as follows:

$$f_3 = \frac{\sum_{1 \le i \le m} d_i}{m} \tag{5}$$

where the percentage of aircraft departing late on a single day is:

$$d_i = \frac{100\left(\sum_{1 \le j \le n_i} \left[\delta_{j,i} > 0\right]\right)}{n_i} \tag{6}$$

The expression enclosed in the square brackets, [ ], is a logical expression. Following Iverson's notation,[18] the value is 1 if the expression is true and zero otherwise. The percentage of aircraft departing early can be determined by subtracting f_3 from 100.

The average amount of delay time for the aircraft that departed late is defined as:

$$f_4 = \frac{\sum_{1 \le i \le m} l_i}{m} \tag{7}$$

where

$$l_i = \frac{\sum_{1 \le j \le n_i} \delta_{j,i} \lfloor \delta_{j,i} > 0 \rfloor}{p_i} \tag{8}$$

and the number of delayed aircraft is:

$$p_i = \sum_{1 \le j \le n_i} \lfloor \delta_{j,i} > 0 \rfloor \tag{9}$$

Similarly, the average amount of early departure time, with respect to the scheduled time of departure, for aircraft that departed early is defined as:

$$f_5 = \frac{\sum_{1 \le i \le m} e_i}{m} \tag{10}$$

where

$$e_i = \frac{\sum_{1 \le j \le n_i} \delta_{j,i} \lfloor \delta_{j,i} \le 0 \rfloor}{q_i} \tag{11}$$

and the number of aircraft that departed early is:

$$q_i = \sum_{1 \le j \le n_i} \lfloor \delta_{j,i} \le 0 \rfloor \tag{12}$$

The average amount of delay for each aircraft delayed fifteen minutes or more is defined as the f_6 measure:

$$f_6 = \frac{\sum_{1 \le i \le m} g_i}{m} \tag{13}$$

with

$$g_i = \frac{\sum_{1 \le j \le n_i} \delta_{j,i} \lfloor \delta_{j,i} \ge 15 \rfloor}{\sum_{1 \le j \le n_i} \lfloor \delta_{j,i} \ge 15 \rfloor} \tag{14}$$

The average delay of those aircraft that had the minimum delay on each day is found as follows:

$$f_7 = \frac{\sum_{1 \le i \le m} a_i}{m} \tag{15}$$

where

$$a_i = \min_{1 \le j \le n_i} (\delta_{j,i}) \tag{16}$$

Similarly, the average delay of the aircraft that had the maximum delay on given days is defined to be:

$$f_8 = \frac{\sum_{1 \le i \le m} b_i}{m} \tag{17}$$

and

$$b_i = \max_{1 \le j \le n_i} (\delta_{j,i}) \tag{18}$$

Two additional metrics, f_9 and f_{10}, for the percentage of aircraft that had delays greater than 15 minutes and 45 minutes are:

$$f_9 = \frac{\sum_{1 \le i \le m} c_i}{m} \tag{19}$$

and

$$f_{10} = \frac{\sum_{1 \le i \le m} h_i}{m} \tag{20}$$

where

$$c_i = \frac{100 \sum_{1 \le j \le n_i} \lfloor \delta_{j,i} \ge 15 \rfloor}{n_i} \tag{21}$$

and

$$h_i = \frac{100 \sum_{1 \le j \le n_i} \left[\delta_{j,i} \ge 45 \right]}{n_i} \tag{22}$$

The metrics f_1 through f_{10} were computed for the departures out of the ten airports listed in Table 1, and a short definition of each metric is available in Table 4. These results are tabulated in the appendix in Table A1. Similar results for the arrival delays for arrivals to the ten airports are given in the appendix, Table A2. Table 5 summarizes the most important metrics: percentage of aircraft delayed more than 15 minutes (f_9), and average delay time of delayed aircraft (f_6).

Comparing the data in Table 5 with the historical statistics in Tables 2 and 3, it is seen that the average amount of delay for each aircraft delayed more than fifteen minutes (f_6) is lower than in Table 2. The percentage of aircraft experiencing more than fifteen minutes of arrival or departure delay (f_9) compares very well with the data in Table 3. The data in Tables A1 and A2 can also be used for ranking the ten airports in order of delay. Table 6 shows the rank based on the average departure delay, the percentage of aircraft departing late and the percentage of aircraft departing later than 15 minutes. Similar ranking is shown using arrival delays and percentage of aircraft arriving later than zero and 15 minutes. Each airport was ranked using the three parameters: f_2 (Eq. (4)), f_3 (Eq. (5)) and f_9 (Eq. (19)) independently, and the average rank was computed to assign the final rank shown in Table 6.

Table 4. Summary of delay metric definitions.

f_1	Avg. number of a/c that departed/arrived in a single day
f_2	Avg. minutes of delay for a single a/c
f_3	Pcnt. of a/c departing/arriving after the scheduled time
f_4	Avg. minutes of delay for a/c defined by metric f_3
f_5	Avg. minutes of delay for a/c not defined by metric f_3
f_6	Avg. minutes of delay for a/c that are later than 15 min.
f_7	Avg. minutes early of the earliest a/c on a given day
f_8	Avg. minutes late of the latest a/c on a given day
f_9	Pcnt. of a/c departing/arriving later than 15 min.
f_{10}	Pcnt. of a/c departing/arriving later than 45 min.

Table 5. Percentage of aircraft delayed more than 15 minutes and the average delay time (minutes) of those aircraft, separated by departures and arrivals.

	Departures		Arrivals	
	Delay (f_6)	Pcnt. Delayed (f_9)	Delay (f_6)	Pcnt. Delayed (f_9)
ATL	30.79	15.37	31.03	13.01
BOS	31.24	15.85	32.09	18.36
DFW	31.33	14.96	30.21	9.86
EWR	33.15	13.48	32.39	14.47
JFK	38.77	18.44	31.18	26.41
LAX	27.82	11.11	29.65	18.47
LGA	32.93	12.38	30.46	12.66
ORD	33.09	19.36	34.25	18.56
SFO	33.85	16.81	32.31	17.61
STL	29.56	12.21	31.36	13.13

Two of the mostly widely used and cited statistics in NAS system analysis are the percentage of aircraft delayed more than fifteen minutes (f_9) and the average delay time of these aircraft (f_6). This is because the FAA reports aircraft as delayed if they depart more than 15 minutes late. Tables 7 and 8 show the percentage of aircraft that had departure delays, arrival delays, and enroute delays, and the average departure delays, arrival delays and enroute delays. The data in Table 7 pertain to the departures from the ten airports. Thus, the departure delays are counted at these airports while the arrival delays are counted at the various destination airports that the departing aircraft flew to. Complementing this, Table 8 shows the data for aircraft that arrived at the ten airports. The arrival delay for these aircraft is counted at the ten airports while the departure delay is counted at the other airports from which these flights originated. The percentage of delayed aircraft is computed as a simple average:

$$f_{11} = \frac{100 \sum_{1 \le i \le m} \sum_{1 \le j \le n_i} \left[\delta_{j,i} \ge 15 \right]}{\sum_{1 \le i \le m} n_i} \tag{23}$$

and the average delay is computed as:

$$f_{12} = \frac{\sum_{1 \le i \le m} \sum_{1 \le j \le n_i} \delta_{j,i} \left[\delta_{j,i} \ge 15 \right]}{\sum_{1 \le i \le m} \sum_{1 \le j \le n_i} \left[\delta_{j,i} \ge 15 \right]} \tag{24}$$

Table 6. Ranking of airports (1 most delayed and 10 least).

Airport	Departures	Arrivals
LGA	1	9
EWR	2	7
JFK	3	1
BOS	4	3
ORD	5	2
DFW	6	10
ATL	7	8
SFO	8	5
LAX	9	4
STL	9	6

Table 7. Percentage of aircraft delayed more than fifteen minutes and length of delay (minutes), selected by departure airport.

	Percent Delayed (f_{11})			Mean Delay Time (f_{12})		
Airport	Dep.	Arr.	Enr.	Dep.	Arr.	Enr.
ATL	16.76	14.24	1.44	30.55	30.99	24.10
BOS	16.90	17.40	4.27	31.58	31.80	26.53
DFW	16.09	15.55	2.87	31.36	30.92	22.39
EWR	14.29	16.15	9.45	31.57	32.28	26.99
JFK	19.12	19.65	6.52	35.52	35.81	27.73
LAX	12.07	17.02	5.23	26.77	26.31	22.46
LGA	13.44	12.29	4.02	31.70	32.27	27.14
ORD	19.93	18.22	4.00	34.38	34.70	21.59
SFO	17.66	22.66	7.94	32.76	31.77	21.94
STL	13.46	19.00	4.87	30.19	29.09	21.55
All 10	16.11	16.79	4.39	31.70	31.43	23.89

Table 8. Percentage of aircraft delayed more than fifteen minutes and length of delay (minutes), selected by arrival.

	Percent Delayed (f_{11})			Mean Delay Time (f_{12})		
Airport	Dep.	Arr.	Enr.	Dep.	Arr.	Enr.
ATL	12.04	14.06	3.08	30.86	29.94	23.40
BOS	14.05	19.41	7.54	31.77	30.83	25.00
DFW	10.71	10.75	2.38	30.66	29.56	19.83
EWR	11.85	15.67	5.79	31.87	31.64	25.54
JFK	16.82	28.26	16.44	32.17	30.53	26.40
LAX	16.19	20.09	3.16	30.70	29.25	22.68
LGA	13.69	13.60	2.13	30.88	30.64	20.01
ORD	15.22	18.58	5.95	33.49	34.05	26.37
SFO	19.30	18.27	4.95	31.10	32.16	25.96
STL	11.45	14.01	1.88	32.52	31.27	27.36
All 10	13.67	16.32	4.46	31.64	31.10	24.78

The departure delays, arrival delays and enroute delays in Tables 7 and 8 are determined following the definitions of f_{11} and f_{12} in Eqs. (23) and (24). These tables show that the arrival delay times are strongly correlated to the departure delay times. This data again indicates arrival delay is similar in magnitude to the departure delay. The data also show fewer aircraft are delayed enroute compared to departing or arriving aircraft.

In addition to the metrics discussed so far, the mean and standard deviation are important features of the delay distribution. The mean of the distribution is determined as:

$$f_{13} = \frac{\sum_{1\le i\le m} \sum_{1\le j\le n_i} \delta_{j,i}}{\sum_{1\le i\le m} n_i} \tag{25}$$

and the standard deviation, assuming a normal distribution, is determined as:

$$f_{14} = \sqrt{\frac{\sum_{1\le i\le m} \sum_{1\le j\le n_i} \left(\delta_{j,i} - f_{13}\right)^2}{\left(\sum_{1\le i\le m} n_i\right) - 1}} \tag{26}$$

The mean and standard deviation of the departure, arrival and enroute delays are given in Tables 9 and 10. Table 9 shows the data for the departures from the ten airports while Table 10 shows the data for the arrivals to the ten airports. The departure delay means in both tables show a positive bias, suggesting congestion at the airports results in more late departures than early ones. These tables show a part of the departure delay is absorbed in the enroute phase, which results in a smaller arrival delay. On average, the standard deviation value of departure delays out of these airports is 16 minutes and for arrival delays into these airports is 18 minutes.

Table 9. Mean and standard deviation of delays (in minutes), selected by departure airport.

	Mean (f_{13})			Standard Deviation (f_{14})		
Airport	Dep.	Arr.	Enr.	Dep.	Arr.	Enr.
ATL	5.17	0.41	-4.75	14.96	17.05	8.63
BOS	4.02	-0.43	-4.33	16.03	20.56	13.23
DFW	3.89	1.20	-2.68	15.64	17.22	9.21
EWR	1.06	-0.29	-1.24	17.21	19.80	14.26
JFK	5.03	-2.94	-7.96	19.18	26.00	18.11
LAX	2.65	2.78	0.18	11.92	14.84	9.74
LGA	1.19	-4.09	-5.23	16.49	19.01	12.05
ORD	5.53	1.34	-4.25	18.34	20.76	11.03
SFO	5.29	4.87	-0.45	16.53	19.30	10.37
STL	3.13	4.85	1.78	14.10	15.99	8.33
All 10	3.91	1.06	-2.82	16.01	18.75	11.20

Table 10. Mean and standard deviation of delays, selected by arrival airport.

	Mean (f_{13})			Standard Deviation (f_{14})		
Airport	Dep.	Arr.	Enr.	Dep.	Arr.	Enr.
ATL	3.50	1.73	-1.76	13.36	15.73	8.74
BOS	2.67	1.93	-0.74	15.54	18.75	11.20
DFW	1.60	-0.80	-2.41	13.36	14.86	8.73
EWR	1.81	0.24	-1.56	14.70	18.29	11.07
JFK	4.19	5.86	1.64	16.56	20.33	15.08
LAX	4.84	3.59	-1.23	14.81	18.29	11.36
LGA	3.46	0.01	-3.44	14.37	16.94	9.19
ORD	3.27	2.52	-0.57	17.09	19.97	11.02
SFO	5.50	-0.35	-5.93	16.15	21.28	14.46
STL	1.67	2.34	0.73	14.74	16.15	7.52
All 10	3.14	1.59	-1.51	15.00	17.84	10.60

Overall Trends

In the previous section, traffic delay characteristics at the ten airports were examined using several metrics. In this section the focus is on aggregate statistics derived from the complete dataset, which includes all the traffic from the ten airports over the 21-day period.

Figure 4 shows the percentage of aircraft as a function of departure and arrival delays. For example, the first light colored bar shows the percentage of aircraft, out of all the aircraft that departed from the ten airports over the 21-day period, that had more than 10 minutes of delay. The first solid bar shows the percentage of arrivals that had more than 10 minutes of delay. Note that departure delays are computed at the ten airports while the arrival delays are computed elsewhere (destination airports). The second set of bars show the percentage of aircraft that had more than 15 minutes of delay and so on. Observe from the figure that a slightly greater percentage of aircraft encounter arrival delays than experience departure delays. This may be due to those aircraft that experienced departure delays, which propagate through to become arrival delays, and those small number that did not experience departure delays but were subject to enroute delays or terminal delays, becoming arrival delays. It should be noted that the difference between the percentages of delayed departures and arrivals is rather small (less than 2), implying that most of the delay originates before departure.

The average number of departures out of the ten airports as a function of the day of the week is shown in Fig. 5. To create the bar charts, the number of departures from the ten airports were summed up for one day of the week (for example, Wednesdays), and divided by the number of such days (number of Wednesdays in the 21-day dataset). The bar chart shows that traffic is less on Sundays, Wednesdays and Saturdays. It should however be noted that the difference between the minimum traffic on Sundays and the maximum traffic on Thursdays is only 9.8%.

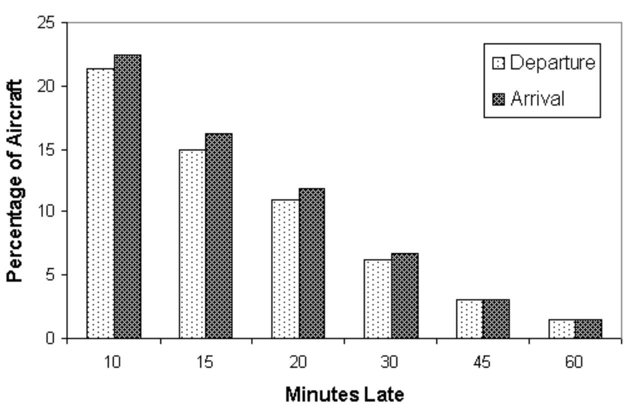

Fig. 4 Percentage of departure aircraft as a function of their departure and arrival delays.

For each day of the week in the 21-day dataset, all departures from the ten airports that were delayed by more than 15 minutes were used to generate the bar charts in Fig. 6. The average percentage of aircraft delayed by more than 15 minutes was found to be 15.0%. This number agrees well with the average of the delayed departure percentages given in Table 3, and shows the variation from day to day is small. Observe that although the traffic volume is lower on Sundays (see: Fig. 5), the percentage of delayed aircraft in Fig. 6 is higher on Sundays. This trend is reversed on Tuesdays. A likely explanation for such a trend is the small variation in departures from day to day is not enough to reach a capacity threshold that will increase the number of delayed aircraft.

Of all the aircraft that experienced delays greater than 15 minutes, their average delay is shown as a function of the day of the week in Fig. 7. It may be seen that the average delay is maximum on Wednesday, although the traffic is higher on Tuesdays and Thursdays. The variation in delay from day to day is small, and the average delay was found to be 32 minutes.

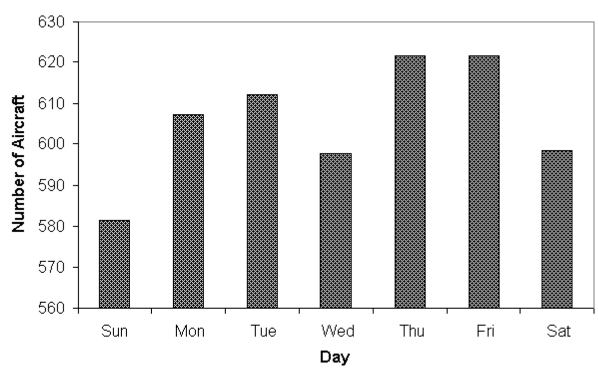

Fig. 5 Average number of departures as a function of day of week.

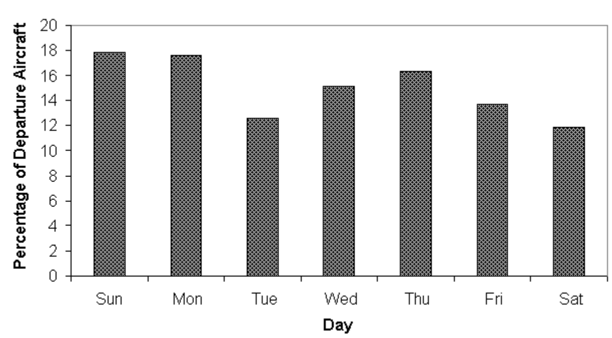

Fig. 6 Percentage of departures delayed by more than 15 minutes.

The trends for aircraft originating at other airports and arriving at the ten chosen airports were found to be similar to those shown in Figs. 6 and 7. The average percentage of arrivals delayed by more than 15 minutes for any given day of week was found to be 16% (compared to 15% for departing aircraft in Fig. 6). The average arrival delay for these aircraft was found to be 32 minutes, which is the same as that found for departing aircraft in Fig. 7.

Delay Modeling

Delay can be modeled by assuming it to be a random variable that follows a statistical distribution. It can also be modeled via an Autoregressive Moving Average (ARMA) model based on past observations of delay or by establishing correlations with respect to predictable quantities. For example, it may be possible to predict departure delay as a function of departure demand. Only the first approach of modeling delay using density functions is described in this paper.

To model departure delay for probabilistic demand forecasting methods, density functions were created using departure and arrival data for the ten airports over the 21-day period. The density functions are defined at each delay time as the *proportion* of all aircraft that departed or arrived that number of minutes late or early. A Normal density function was then computed from the mean and standard deviation of the raw distribution, and a least squares error minimization was performed to improve the fit with respect to the actual density function. A Poisson density function was also computed and error with respect to the actual density function was minimized. A Poisson distribution was found to better model departure delays, while a Normal distribution modeled enroute and arrival delays better.

Figure 8 shows the density functions for departure delays, enroute delays and arrival delays for aircraft that departed from the ten airports. The departure delays are computed at the ten airports and the arrival delays are computed at their destination airports. Similar density functions are shown in Fig. 9 for all the aircraft that arrived at the ten airports. The arrival delays are computed at the ten airports while the departure delays are computed at the airports of origin. Observe that the density functions look similar in both the figures. Departure delay, enroute delay and arrival delay distributions at several individual airports were also found to be very similar to the average characteristics shown in Figs. 8 and 9. This suggests that the distributions plotted are representative of all airports, not just the ten in the study.

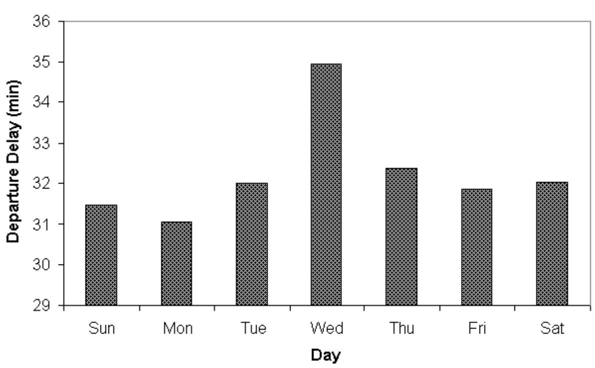

Fig. 7 Average departure delay for aircraft delayed by more than 15 minutes.

The mean departure delay, enroute delay and arrival delay for departing aircraft (Fig. 8) were (a) 3.91 minutes, (b) -2.83 minutes and (c) 1.06 minutes. The mean departure, enroute and arrival delays for arriving aircraft (Fig. 9) were (a) 3.14 minutes, (b) -1.51 minutes and (c) 1.59 minutes. It should be noted that the average arrival delay is approximately the sum of the average departure and enroute delays. Observe that the arrival delay density function is diffuse compared to the departure and enroute delay density functions.

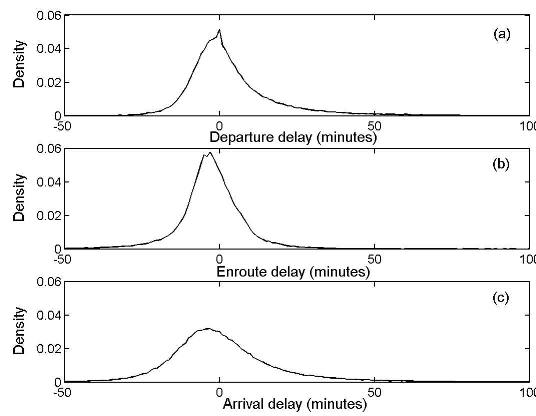

Fig. 8 Density functions for departing aircraft.

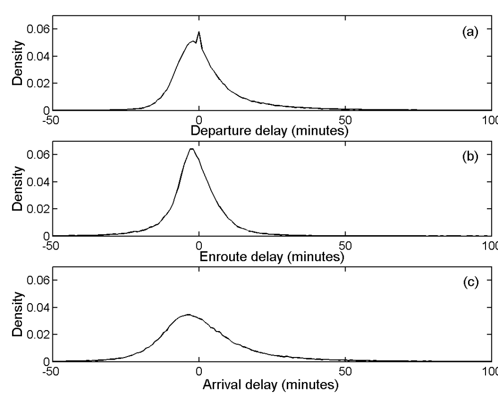

Fig. 9 Density functions for arriving aircraft.

To model the departure distribution in Fig. 8a, a Normal distribution is assumed. The equation for this distribution is:

$$P(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{27}$$

where μ is the mean of the distribution and σ is the standard deviation. The mean of the departure distribution in Fig. 8 is 3.91 minutes and the standard deviation is 16 minutes; however the raw departure density function and the Normal density function with the same mean and standard deviation do not coincide.

To improve the delay model one can adjust the standard deviation and the mean by computing a perturbation about the nominal distribution as follows. Let the mean and the standard deviation of the nominal Normal distribution be $\overline{\mu}$ and $\overline{\sigma}$. The perturbation equation can be obtained in terms of the nominal mean and standard deviation as:

$$dP = \frac{1}{\sqrt{2\pi}\overline{\sigma}} e^{-\frac{(x-\overline{\mu})^2}{2\overline{\sigma}^2}} \left[\left(\frac{x-\overline{\mu}}{\overline{\sigma}^2} \right) d\mu + \left(\frac{(x-\overline{\mu})^2}{\overline{\sigma}^3} - \frac{1}{\overline{\sigma}} \right) d\sigma \right] \tag{28}$$

where *dP* is the error between the Normal density function and the raw density function at each delay time instant. Since an equation of the form given in Eq. (28) can be set up at each sampling instant, $d\mu$ and $d\sigma$ can be computed using the Least Squares method. For the given data-set, $d\mu$ and $d\sigma$ were found to be -5.45 minutes and -5.52 minutes. These corrections resulted in the mean of -1.54 minutes and standard deviation of 10.49 minutes. The resulting Normal distribution is shown in of Fig. 10. The improvement in fit error, measured as the sum of the squares of the errors, is 71% compared to the nominal Normal distribution.

To determine if another model would better fit the data, a Poisson distribution model is examined next. If a random variable X has a Poisson distribution, its density function $P(X = x)$ is:

$$P(x) = \frac{e^{-\mu} \mu^x}{x!} \tag{29}$$

where the mean $\mu > 0$.[19] The Poisson density function is plotted along with the raw departure density function in Fig. 11a.

To improve the error with respect to the raw distribution, the mean μ can be adjusted by using the Least Squares method. Let $\overline{\mu}$ be the mean delay derived from the data. The correction to the mean can be computed in terms of the perturbation about the nominal Poisson distribution as:

$$dP = \frac{e^{-\overline{\mu}} \overline{\mu}^x}{x!} \left(\frac{x}{\overline{\mu}} - 1 \right) d\mu \tag{30}$$

With *dP* as the error between the Poisson density function and the raw density function at each discrete delay time instant, the Least Squares solution resulted in $d\mu$ of -3.98 minutes. Adding this correction to the nominal mean of 3.91 minutes resulted in -0.07 minutes. (The condition forbidding a negative mean can be avoided by a simple shift in the domain.) The density function using a Poisson model with this value of the mean is shown in Fig. 11b. The best-fit Poisson distribution (Fig. 11) shows an improvement 38% over

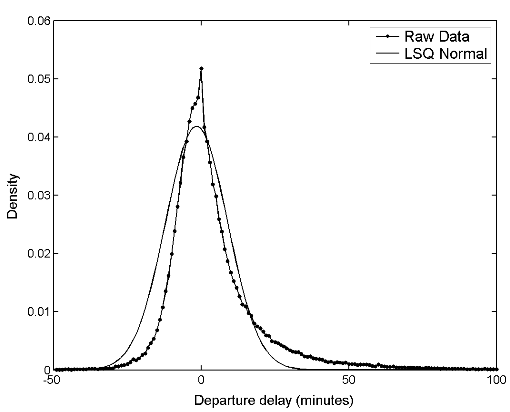

Fig. 10 Least Square Normal distribution model for departure delays.

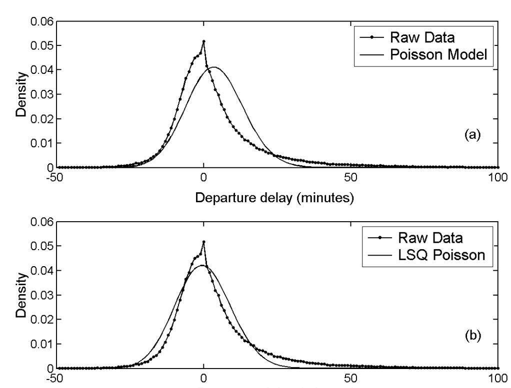

Fig. 11 Departure delay modeled using Poisson distributions.

the best-fit Normal distribution model (Fig. 10). The fit error is measured as the sum of the squares of the errors of all the samples. In conclusion, the Poisson distribution model describes the departure delay distribution more accurately than the Normal distribution model.

Enroute delay data, shown in Fig. 8, were also modeled using Normal and Poisson density functions. Figure 12 shows the Normal density function obtained by using the Least Squares technique using Eq. (28). The mean and the standard deviation values of -2.82 minutes and 11.20 minutes of the nominal Normal distribution were corrected by 0.36 minutes and -3.82 minutes which resulted in the mean and standard deviation values of -2.46 minutes and 7.38 minutes. The best-fit Normal density function reduced the fit error by 83% compared to that obtained using the nominal Normal density function. The best-fit Poisson density function could only lower the error by 53% compared to that obtained using the nominal Normal density function. Thus, the enroute delay distribution was modeled best by the Normal distribution.

The arrival delay data, shown in Fig. 8, were modeled using the Normal density function and the Poisson density function. Best-fit was achieved with the Normal density function, as shown in Fig. 13, using the distribution whose mean and standard deviation were adjusted through Eq. (28).

The mean and standard deviation of the nominal Normal distribution were 1.06 minutes and 18.74 minutes. Error minimization with respect to the raw arrival delay density function using the Least Squares method resulted in corrections of -3.79 minutes to the mean and -4.99 minutes to the standard deviation. The adjusted Normal distribution shown in Fig. 13 (LSQ Normal) has a mean of –2.73 minutes and a standard deviation of 13.75 minutes. The best-fit Normal distribution reduced the fit error by 78% compared to the nominal Normal distribution.

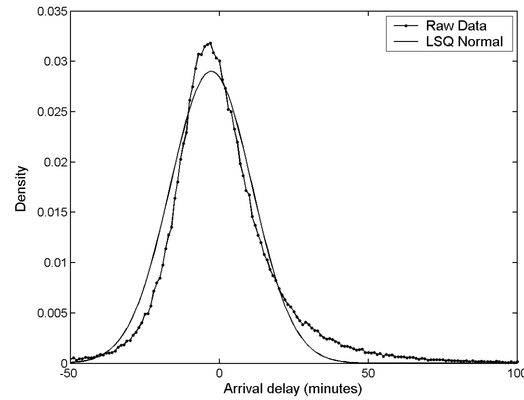

Fig. 13 Arrival delay modeled using a Normal distribution.

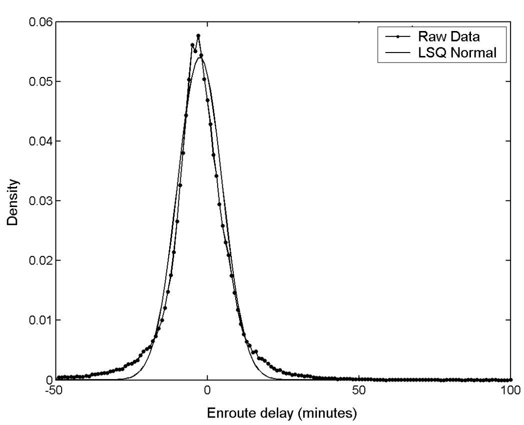

Fig. 12 Enroute delay modeled using a Normal distribution.

Using Normal distribution models for the data in Fig. 8 shows that the standard deviation of enroute delay (7.38 minutes) is smaller than the standard deviation of departure delay (10.49 minutes), which is smaller than the standard deviation of arrival delay (13.75 minutes).

Similar results were also obtained for data shown in Fig. 9. Modeling of the departure delay density function using Normal and Poisson distributions revealed that a better fit is obtained using a Poisson distribution. The improvement in fit-error is 12% over modeling with the Normal density function. Best-fit solutions for enroute delay and arrival delay modeling were obtained using Normal density functions.

5. Conclusions

This paper was devoted to the analysis of departure, enroute and arrival delays of aircraft that operated out of one of ten major U.S. hub airports with the objective of improving delay prediction. To put the results in perspective, historical delay data for these airports from past studies were summarized. Causal factors for the delays related to aircraft, airline operations, change of procedures and traffic volume were identified. All the results of delay analysis were based on traffic data derived from the Post Operations Evaluation Tool (POET) database for the ten airports in a 21-day period. Delay metrics, described in the paper, were computed for a typical day by first averaging for a day of operations and then averaging the result over the 21 days. The numerical results for the average duration of departure delay were found to be smaller than the historical delays, but the percentage of aircraft that experience departure or arrival delays was found to be in good agreement with the historical trends. The delay metrics were also used to rank the ten airports. LGA was ranked worst in departure delays while JFK ranked worst in arrival delays. The next two most delayed for departures were EWR and JFK, and for arrivals ORD and BOS. In addition to the delay characteristics of individual airports, aggregate statistics were derived from the complete dataset and presented as functions of the days of the week. It was shown that the percentage of aircraft delayed more than the FAA standard of 15 minutes was in agreement with the historical data. A small amount of variation was seen in the average number of departures, percentage of delayed departures and average departure delay (for the delayed aircraft) as a function of the day of the week. Stochastic modeling of delays was attempted by creating probability density functions using all the data over the 21-day period. The density functions were modeled using Normal and Poisson distributions based on the mean and standard deviations derived from the raw data, and were then improved by adjusting the mean and standard deviation values via a Least Squares method. It was shown that departure delay is modeled better using a Poisson distribution while the enroute and arrival delays are modeled better using Normal distributions. These models can be used to improve the accuracy of probabilistic departure time or sector arrival time forecasts.

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Appendix

Table A1. Basic metrics for all aircraft that departed from the specified airports.

Departures	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}
ATL	1033	5.06	55.83	13.18	-5.29	30.79	-72.38	114.57	15.37	2.72
BOS	425	3.84	49.73	14.34	-6.86	31.24	-91.17	88.05	15.85	3.00
DFW	890	3.85	48.69	14.10	-6.02	31.33	-42.62	125.29	14.96	2.62
EWR	430	1.28	43.82	14.75	-9.33	33.15	-56.98	129.69	13.48	2.59
JFK	254	5.85	49.42	18.98	-7.21	38.77	-42.67	168.10	18.44	5.05
LAX	727	2.57	48.83	10.73	-5.31	27.82	-101.17	112.95	11.11	0.93
LGA	390	1.34	43.37	14.22	-8.58	32.93	-51.29	118.00	12.38	2.34
ORD	1063	6.08	50.57	17.11	-6.60	33.09	-147.57	122.81	19.36	5.05
SFO	336	5.61	53.93	14.93	-5.50	33.85	-45.95	129.19	16.81	3.62
STL	509	3.16	47.21	12.39	-5.60	29.56	-50.57	101.00	12.21	2.12

Table A2. Basic metrics for all aircraft that arrived at the specified airports.

Arrivals	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}
ATL	973	1.67	45.78	13.46	-8.46	31.03	-189.62	167.69	13.01	2.25
BOS	424	1.86	46.05	17.29	-11.48	32.09	-134.60	178.19	18.36	2.97
DFW	830	-0.91	37.97	12.45	-9.10	30.21	-99.31	124.29	9.86	1.48
EWR	424	0.07	41.86	16.09	-11.52	32.39	-146.69	129.40	14.47	2.66
JFK	262	4.47	55.87	18.95	-13.85	31.18	-233.29	100.86	26.41	4.09
LAX	670	3.24	53.54	15.41	-10.96	29.65	-238.83	123.81	18.47	2.65
LGA	378	-0.08	42.03	13.99	-10.51	30.46	-108.90	95.57	12.66	2.13
ORD	1075	3.75	45.64	18.56	-10.62	34.25	-197.71	157.81	18.56	4.70
SFO	355	-0.27	42.09	17.63	-13.43	32.31	-88.33	96.33	17.61	3.49
STL	533	2.41	47.71	13.59	-8.25	31.36	-137.62	138.00	13.13	2.63