METHODOLOGY FOR ESTIMATING AIRPORT CAPACITY AND THROUGHPUT PERFORAMNCE USING PDARS

Yu Zhang
National Center of Excellence for Aviation Operations Research (NEXTOR)
University of California at Berkeley
107A McLaughlin Hall, Berkeley, CA 94720
Phone: (510) 642-5896 Fax: (510) 642-5687
zhangyu@berkeley.edu

Jasenka Rakas
National Center of Excellence for Aviation Operations Research (NEXTOR)
University of California at Berkeley
107B McLaughlin Hall, Berkeley, CA 94720
Phone: (510) 642-9064 Fax: (510) 642-5687
jrakas@berkeley.edu

Eric Liu
National Center of Excellence for Aviation Operations Research (NEXTOR)
University of California at Berkeley
107A McLaughlin Hall, Berkeley, CA 94720
Phone: (510) 642-5896 Fax: (510) 642-5687
ericliu@berkeley.edu

METHODOLOGY FOR ESTIMATING AIRPORT CAPACITY AND THROUGHPUT PERFORAMNCE USING PDARS

ABSTRACT

This study develops a methodology for assessing airport performance and establishing airport efficiency metrics for runway and airport utilization. We focus on the estimates of landing time intervals for each consecutive pair of aircraft for each runway and then aggregate micro aircraft-landing data to runway level, airport-configuration level and airport level. By combining two databases, Performance Data Analysis Reporting System (PDARS) and Aviation System Performance Metrics (ASPM), we are able to explicitly consider traffic mix, the effects of traffic demand and the impact of weather conditions on landing time intervals. A normal-lognormal probability distribution for landing time intervals is introduced. The performance of the proposed distribution and probability distributions found in the existing literature are compared for five major airports in the U.S. Then, we develop a comprehensive methodology for reliably estimating airport performance and establishing airport-efficiency metrics for runway and airport utilization. The proposed methodology should assist the FAA System Capacity Office in improving measurement and analysis of airport performance. Furthermore, if integrated into ATAC's PDARS tool, the proposed methodology would improve estimation of airport performance and could be automated for daily reporting.

Keywords: Airport performance, Airport capacity, Performance Data Analysis Reporting System (PDARS), Statistical modeling

1. INTRODUCTION

Airport performance measurement is a very important mechanism for understanding, monitoring and managing airport operations on a daily basis. It can also be used for predicting future operational problems and introducing effective measures to avoid potential problems by introducing new operational concepts, policies or technologies. Measurement of airport performance can also be useful in evaluating and determining the best investment strategies towards modernization, expansion or reconstruction of airports and the updates of airport master plans. It is also very useful to regulatory bodies, governments and other stakeholders such as passengers and airlines [*1*]. Airport performance measurement has to be designed to reflect demand growth, regulations, technical innovations, and air traffic control procedural upgrading. Measurement of airport performance has attracted significant attention in last two decades and a number of different metrics have been developed, such as capacity, delay and safety – just to mention the most basic metrics. Other conventional metrics include, but are not limited to aircraft throughput, passenger throughput and runway occupancy time.

Aircraft separation, as an airport performance metric, was recently analyzed in great detail with the objective to explore safety and capacity issues at the same time [*2*]. The authors performed statistical analyses on the landing time intervals to explore the operational properties of the Los Angeles International Airport (LAX) by using the data from Performance Data Analysis and Reporting System (PDARS). Their proposed distribution assumption better approximated the shape of the landing time interval histogram from real data, especially the left-hand side, which was considered more important regarding airport safety and capacity. Because PDARS allows a precise calculation of landing time intervals on a runway level for each aircraft pair assigned to a particular runway, it was possible to perform airport performance analysis on a micro-level.

In this study, we develop a methodology that transfers the landing time interval analyses for individual runways to airport performance measurement. We postulate that the probability distribution of landing time intervals is not universal for all airports across the National Airspace System (NAS), but that it might vary with the number and complexity of runway layouts and runway configurations in use, weather conditions, traffic demand, aircraft mix or air traffic control "culture" deployed at an airport. We explore differences at five major PDARS airports by using PDARS information on aircraft-runway assignments and translate the micro-level (i.e., individual runway) analyses to the runway-configuration level and then – to the airport aggregate level. By exploring such levels, this paper differs from any previous work, since most of the airport performance analyses have been modeled on the airport (aggregate) level.

2. METHODOLOGY

The methodology in this study includes a comparison of four distribution assumptions for five airports in PDARS data base and proposes a comprehensive landing time interval (LTI) model based on Vendevenne model [*3*].

The comparison of distribution assumptions focuses on a large aircraft trailing a large aircraft at Dallas Forth Worth (DFW) under visual meteorological conditions (VMC) with wind speed less than 10 nm. Aviation System Performance Metrics (ASPM) data is combined with PDARS, providing information of meteorological conditions and the wind speed. LTIs are calculated for each consecutive pair of aircraft for each runway and then they are merged to obtain a statistically larger sample. After that, the maximum likelihood estimators are calculated to find the best probability distribution of the landing time intervals. Maximum likelihood value of distribution assumptions are compared as well as the computational difficulties.

In the next step, a comprehensive model is proposed. Linear functions are constructed to take into account the characteristics of the air traffic controller target separation and airport demand variation. The target separation is not only dependent on the character of aircraft pairs and meteorological conditions, but also on runway configurations, which capture wind patterns not reflected by meteorological conditions. In other words, target separation for a large aircraft trailing another large aircraft could be different from one runway-configuration to another even if all other circumstances are the same. Logic based on runway layouts is assumed to distribute arrival demand to different runways according to their functions under a particular configuration. Dummy variables are added to indicate different runway configurations, meteorological conditions, and aircraft mix.

2.1. PDARS and ASPM Database Description

Performance Data Analysis and Reporting System (PDARS) database is supported by radar track and flight plan information directly from Automatic Radar Terminal System (ARTS) computers at Terminal Radar Approach Control (TRACON) facilities, and from the Host computers at Air Route Traffic Control Centers (ARTCCs). A combination of these two databases provides, through PDARS, a very precise description of each flight every two seconds. For the purpose of this research, information on aircraft-runway assignments, aircraft threshold times, aircraft type and category and airline are used.

Aviation System Performance Metrics (ASPM) database contains more than 90 fields, including information such as actual and estimated arrival and departure times, gate and taxi times, and en route performances. The FAA’s Office of Aviation Policy and Planning uses ASPM data for airport efficiency analyses on a yearly, monthly, and daily level. For the purpose of this research, the on-line database was used to obtain information about arrival demand, runway configuration in use, and meteorological conditions (Instrument Flight Rules (IFR), Marginal Visual Flight Rules (MVFR) and Visual Flight Rules (VFR)).

2.2. Description of the Study Area

Airports in this study include five largest airports (Figure 1) in Terminal Approach Radar Controls (TRACONs) where PDARS data are available: Dallas Fort Worth International Airport (DFW), Los Angeles International Airport (LAX), George Bush Intercontinental/ Houston Airport (IAH), San Francisco International Airport (SFO), and Phoenix Sky Harbor International Airport (PHX) from TRACONs D10, I90, NCT, SCT, and P50, respectively. These five airports are among the busiest airports in the U.S. The ranks of these airports in terms of passenger enplanements and aircraft operations in calendar year

2001 are listed in Table 1. Percentage changes from year 2001 to forecast in year 2013 are shown in the right two columns of Table 1 [*4*].

Table 1. Aviation Statistics

	Rank in 2001		2001		Forecast 2013	
	Passenger Enplanements	Aircraft operation	Passenger Enplanements (Million)	Aircraft operation (Thousand)	Passenger Enplanements	Aircraft operation
DFW	4	3	25.6	802.6	34.4%	25.6%
LAX	3	4	29.4	738.7	21.4%	4.5%
PHX	5	5	17.5	606.7	37.2%	13.2%
IAH	9	11	16.2	477.4	48.1%	27.4%
SFO	8	23	16.5	387.6	14.5%	-5.3%

Figure 1 shows the layouts of those multi-runway airports [*4*]. The number and geometry of multi-runway layouts differ significantly among airports. For example, SFO has two sets of intersecting closely-spaced parallel runways that prohibit simultaneous arrivals or departures. The other airports contain either coupled, widely-spaced parallel runways (LAX, PHX) or several sets of parallel runways (DFW, IAH, PHX). The benchmark capacities of these airports are summarized in Table 2 [*5*].

Table 2. Benchmark Capacities of Study Airports

	Optimum rate[1]	Marginal rate[2]	IFR rate[3]
DFW	270-279	231-252	186-193
LAX	137-148	126-132	117-124
PHX	128-150	108-118	108-118
IAH	120-143	120-141	108-112
SFO	105-110	81-93	68-72

[1] Ceiling and visibility above minima for visual approaches (4000ft ceiling and 8mi visibility
[2] Below visual approach but better than instrument conditions
[3] Instrument conditions (ceiling < 1000ft or visibility <3.0mi)

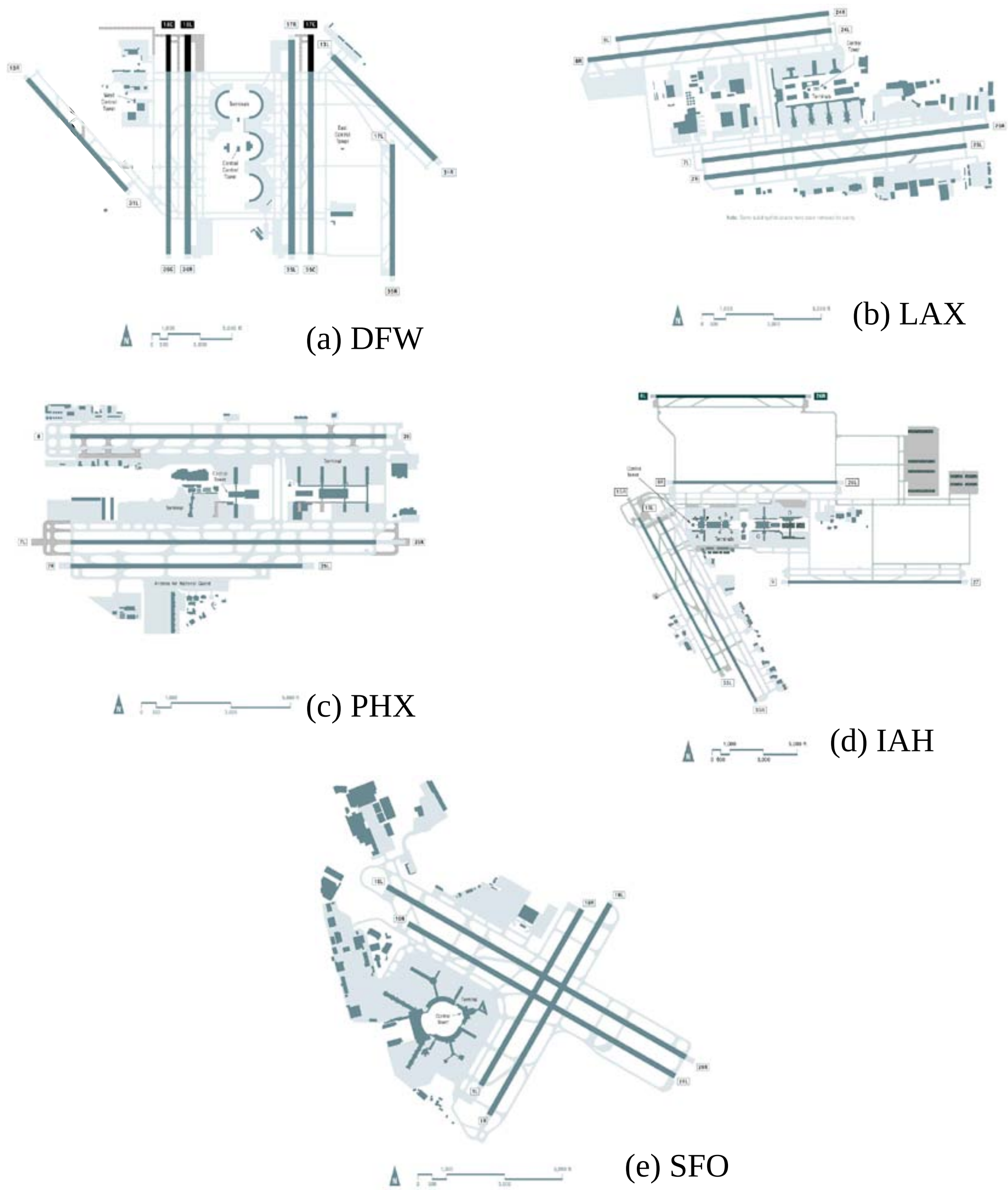

Figure 1. Layout of PDARS Airports

3. STATISTICAL MODELING OF LANDING TIME INTERVALS (LTIs)

Various statistical models were used to examine the observed landing time interval distributions. These include the Normal, Vandevenne, Controlled-Normal, and Normal-Lognormal models.

3.1. Normal

The normal distribution has widely been used previously to model observed landing time intervals, *S*. The normal distribution is described by the probability density function (PDF) in equation (1),

$$f_s(s) = \frac{1}{\sqrt{2\pi\sigma}} e^{\left(\frac{s-\mu}{\sigma}\right)^2} \tag{1}$$

where μ represents the mean and σ represents the standard deviation.

3.2. Vandevenne

The Vandevenne model was developed for landing time interval distributions and takes into account the occurrence of longer separation times when demand is low [*2*]. The model assumes that the actual observed headway, *S*, between two aircraft is composed by the additive components shown in equation (2).

$$S = D + \varepsilon + g \tag{2}$$

D represents a constant headway that air traffic controllers strive to achieve but cannot due to the air traffic controller's imprecision error, ε, and the gap, *g*, that cannot be closed with the available control. The imprecision error is assumed to be normally distributed as N(0, σ), where σ is the standard deviation. The gaps that cannot be closed by the air traffic controller follow a negative-exponential distribution when the arrival rate, λ, is assumed to be random and thus, follow a Poisson distribution. The resulting PDF for *S* is described by equation (3).

$$f_s(s) = \lambda e^{\left[-\lambda\left(s - D - \frac{\lambda\sigma^2}{2}\right)\right]} \Phi\left(\frac{s - D - \lambda\sigma^2}{\sigma}\right) \tag{3}$$

Φ represents the cumulative density function (CDF) for the standard normal distribution while *s* represents a single headway observation between two aircraft. The parameters estimated in this model are *D*, σ, and λ.

3.3. Controlled-Normal

The Controlled-Normal model, derived from previous work [2], was also employed to examine the observed landing time intervals. In this model, the headways of aircraft are assumed to follow a normal distribution with a mean of μ_1 and a standard deviation of σ_1. A critical threshold *C* is presented; air traffic controllers will take action to adjust the headway if it is below *C*. Conversely, if the headway is greater than *C*, air traffic controllers consider this safe and thus, take no action. As a result, the controlled headways follow a new normal distribution. This model is illustrated in Figure 2 below and explained in [*2*].

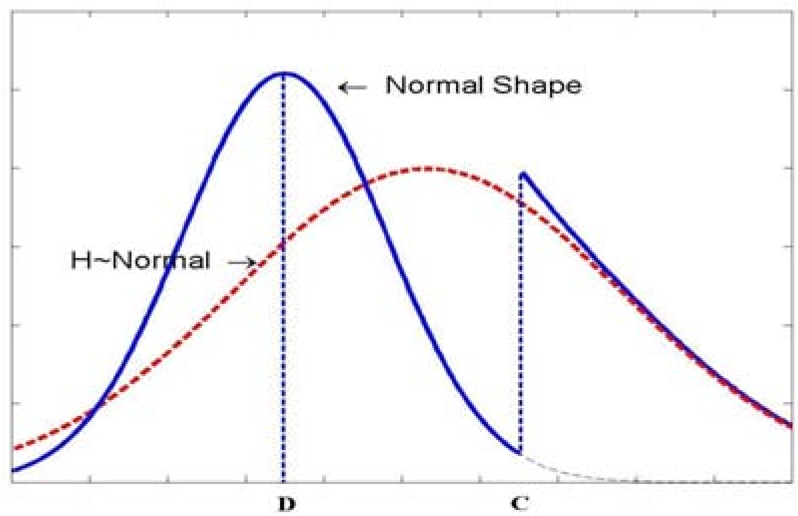

Figure 2. Controlled-Normal Model

The dotted (red) line illustrates the assumed normal distribution that aircraft headways follow when they arrive without any control. The (blue) solid line to the right of *C* represents the headways where air traffic controllers take no action. Conversely, the scaled narrower curve to the left of *C* represents the headways that controllers adjust, which follow a new normal distribution. This normal distribution has a mean of *D*, the ideal headway that air traffic controllers try to achieve, and a standard deviation of σ_2. Together the complete (blue) solid line represents the observed headway, *S*, which has a PDF denoted by equation (4).

$$f_S(s) = \begin{cases} \Phi_1(C) \times \phi_2(s), & \text{if } s \le C \\ \Phi_1(C) \times \phi_2(s) + \phi_1(s), & \text{otherwise} \end{cases} \tag{4}$$

$\Phi_1(C)$ represents the CDF of a headway before any control is given, while $\phi_1(s)$ represents the PDF of a headway before any control is given. Subsequently, $\phi_2(s)$ represents the PDF of a headway on the scaled normal distribution that has a mean of D. The parameters estimated in this model are $\mu_1, \sigma_1, \mu_2, \sigma_2$, and C.

3.4. Normal-Lognormal

Similar to the Controlled-Normal model, the Normal-Lognormal model uses some of the same assumptions regarding a critical threshold and controller adjustment. However, instead of assuming headways adjusted by air traffic controllers follow a new normal distribution, the Normal-Lognormal model assumes they follow a lognormal distribution. The rationale behind this assumption was that the log-normal distribution eliminates values below 0 in the PDF; thus, this is a more accurate formulation of the model since headways are non-negative. In addition, a thicker tail on the right side in the log-normal distribution seems to produce a better fit with the observed landing time interval distributions. The PDF for the observed headway, *S*, using the Normal-Lognormal model is described in equations (5) and (6).

$$f_S(s) = \begin{cases} \Phi(C) \times f(s), & \text{if } s \le C \\ \Phi(C) \times f(s) + \phi(s), & \text{otherwise} \end{cases} \tag{5}$$

$$where: \quad f(s) = \begin{cases} \dfrac{\exp\left(-\dfrac{1}{2}\left(\dfrac{\log(s) - m}{t}\right)\right)}{st\sqrt{2\pi}}, & s > 0 \\ 0, & otherwise \end{cases} \tag{6}$$

$\Phi_1(C)$ again represents the CDF of a headway before any control is given, while $\phi(s)$ represents the PDF of a headway before any control is given. The variables μ and σ denote the mean and standard deviation of the normally distributed headways before any control, respectively. Subsequently, the variables *m* and *t* denote the mean of the log of *S* and the standard deviation of the log of *S*, respectively. The parameters estimated in this model are μ, σ, *m*, *t*, and *C*.

3.5. Results of Statistical Models

The above models were applied to five major airports: DFW, IAH, LAX, PHX, and SFO. The results for the four statistical models presented above for each of the five airports are graphically shown in Figures 3-7. Specifically, the results are for VFR conditions with low winds, large following large aircraft, and the primary runways of each airport.

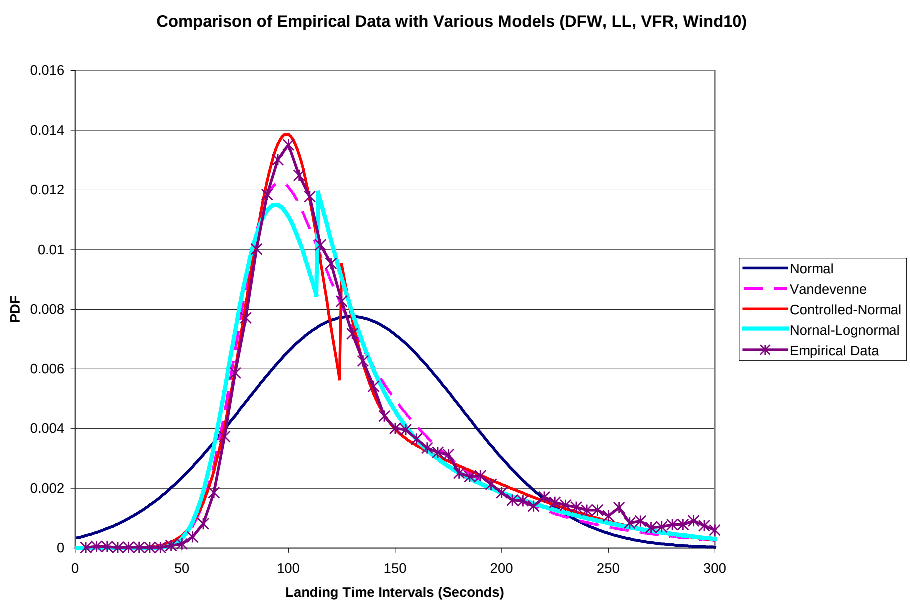

Figure 3. Comparison of Empirical Data for DFW Airport with Proposed Models

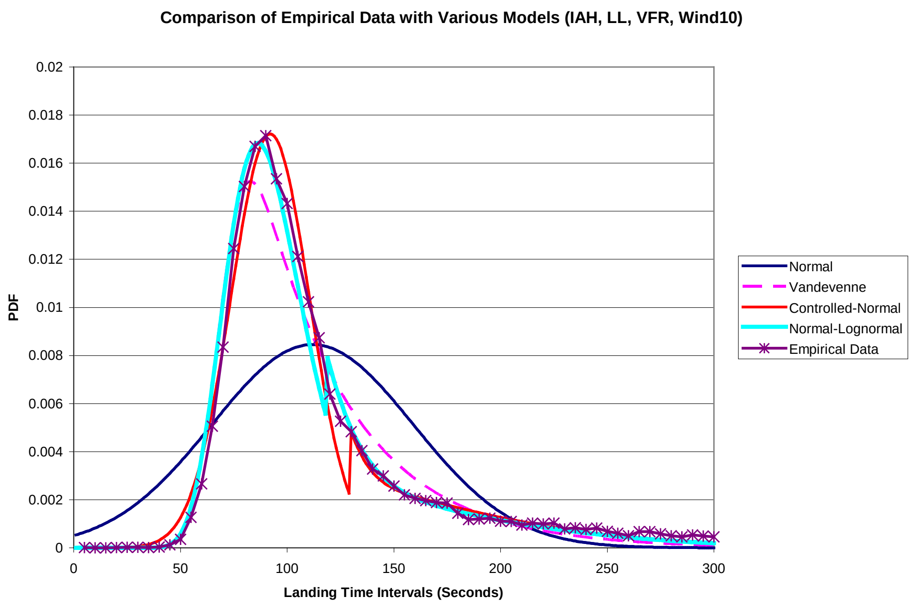

Figure 4. Comparison of Empirical Data for IAH Airport with Proposed Models

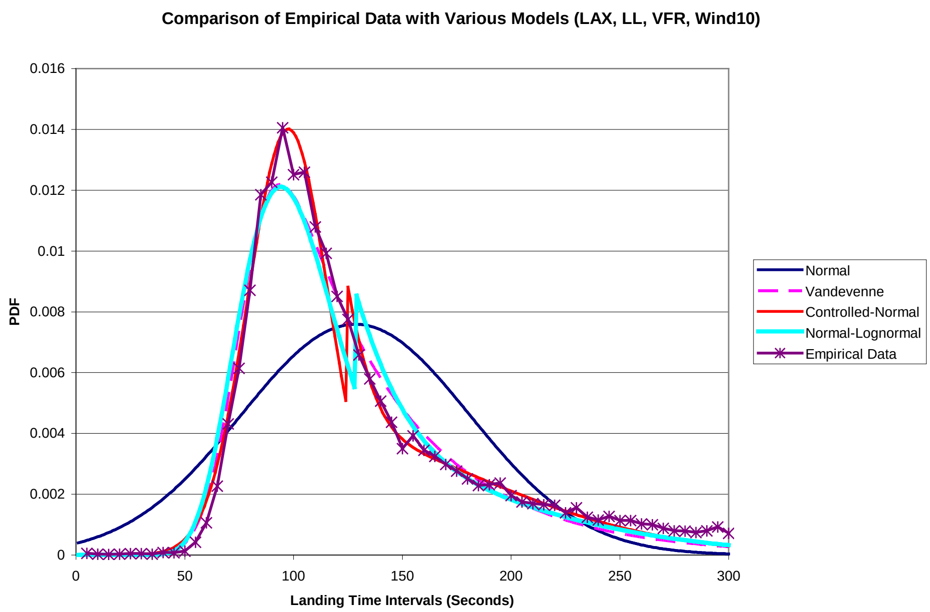

Figure 5. Comparison of Empirical Data for LAX Airport with Proposed Models

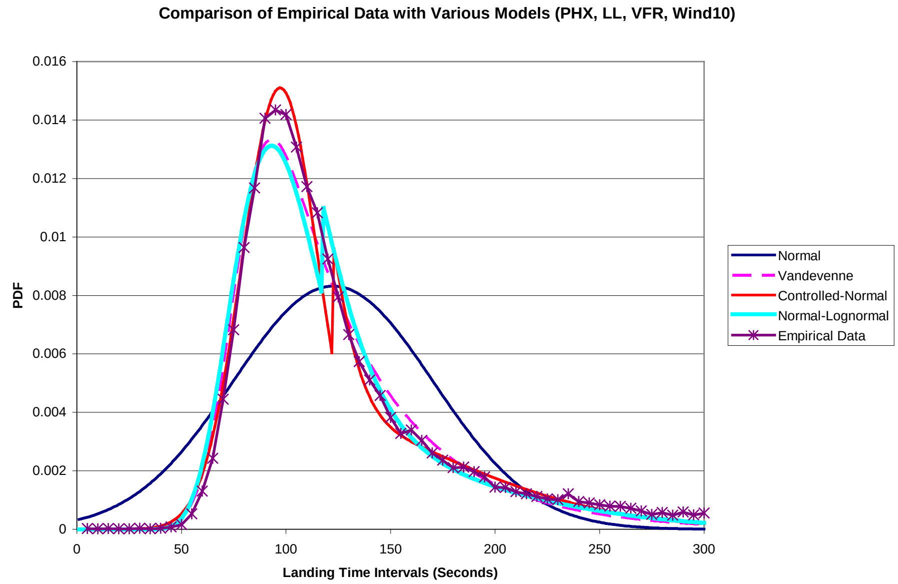

Figure 6. Comparison of Empirical Data for PHX Airport with Proposed Models

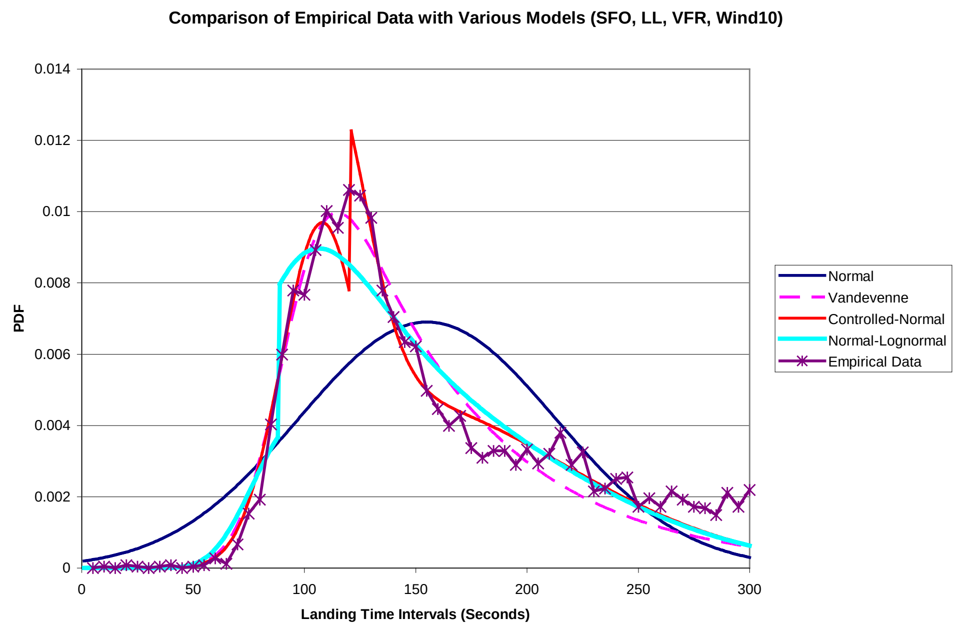

Figure 7. Comparison of Empirical Data for SFO Airport with Proposed Models

The maximum log-likelihood technique was used in order to estimate the parameters for each statistical model. The results reveal that the four models, with the exception of the normal model, fit the observed landing time interval distributions very well, as shown in Table 3.

Table 3. Parameter Estimation of Four Statistical Models

	μ_1	σ_1	μ_2(D)	σ_2	λ	δ	C	LL1	SIC2
Normal			129	53				**-35977**	**71958**
Vandevenne			77		0.02	10.93		**-34543**	**69092**
Controlled-Normal	88	93	105	21			148	**-34513**	**69036**
Normal-Lognormal	28	130	106	26			148	**-34476**	**68962**

Each model is able to capture the overall shape of the observed distribution, though the models for SFO exhibit more variation. However, with the exception of LAX, the sharp shoulder occurring on the right side of the Controlled-Normal and Normal-Lognormal models do not exist for the other four major airports. For LAX, there is a slight shoulder seen at a landing time interval of approximately 150 seconds. In addition, the Controlled-Normal and Normal-Lognormal models have slightly larger maximum log-likelihood values when compared to the Vandevenne model. Nevertheless, the Vandevenne model has more degrees of freedom than these two more complex models and is easier to obtain convergence during optimization. Hence, instead of refining distribution assumption, we now focus on capturing the dynamic characteristics of the parameters in Vendevenne model.

4. COMPREHENSIVE MODEL OF RUNWAY ARRIVAL CAPACITY

In Vendevenne paper, the authors focus on a subset of large-large aircraft pairs under VMC meteorological conditions. A target time separation, D, that an air traffic controller attempted to reach and the average arrival rate of flights, λ, are taken as constants in the model. For an airport with a simple, and only a few runway configurations, this assumption may be valid. However, for an airport with complicated and various runway configurations, the coefficients D and λ are not constant but subject to runway configuration. Usage of runway configurations depends on wind direction and wind speed at the runway. These are not captured by meteorological records and need to be considered carefully.

4.1. Comprehensive Single-Fixed Effect Model of LTIs

In this part of the study, we propose a comprehensive single-fixed effect model of LTIs. In addition to considering the existing large-large aircraft pairs, we investigate all other aircraft-pairs with respect to aircraft type (size) within the existing fleet mix. D is represented by a linear function subject to traffic mix, meteorological conditions, and runway configurations. Distribution logics for demand to different runways are introduced at a particular airport and a linear function is constructed for λ with a given arrival demand from ASPM data. Given LAX as an example with runway configurations shown in figure 1a, the functions of D and λ are defined by equations (7) and (8), respectively:

$$D = a + \gamma_1 \times MVMC + \gamma_2 \times IMC + \sum_{i=2}^{6} w_i \times Rwyconf_i$$
$$+ t_H \times TrailH + t_S \times TrailS + l_H \times LeadH + l_S \times LeadS \qquad (7)$$

Equation 7 has the following variables:

- $MVMC$ and IMC are dummy variables for meteorological conditions. If LTI occurs under marginal VMC condition then $MVMC$ equals to 1, otherwise 0. If it occurs under IMC condition, then IMC equals to 1, otherwise 0.
- $Rwyconf_i$ is the dummy variable indicating runway configurations.
- $TrailH$, $TrailS$, $LeadH$, and $LeadS$ are dummy variables specifying the aircraft types of a sequence pair. If a trailing aircraft is heavy, then $TrailH$ equals to 1, otherwise 0. If a leading aircraft is small, then $LeadS$ equals to 1, otherwise 0. We define $TrailS$ and $LeadH$ similarly.
- γ , w , t , and l are fixed effect coefficients for the above listed dummy variables.

The baseline operating conditions for D are as follows:

(a) large aircraft trailing large aircraft under VMC condition,

(b) runway configuration 24R, 25L | 24L 25R, where runways 24R and 25L are used for arrivals and 24L and 25R are used for departures.

Table 4. Runway Configurations at LAX

No.	Runway Configurations	
	Landing Runways	Takeoff Runways
1	24R, 25L	24L, 25R
2	24L, 24R	25L, 25R
3	24L, 24R, 25L, 25R	24L, 24R, 25L, 25R
4	6L, 7R	6R, 7L
5	6L, 6R	7L, 7R
6	6L, 6R, 7L, 7R	6L, 6R, 7L, 7R

As depicted in figure 1a, there are two sets of parallel runways at LAX. Generally, the outer runways are used for arrivals and the inner runways are used for departures. When the outer runways or one set of parallel runways are only dedicated to arrivals (Table 4: No. 1 and 4; No. 3 and 6, respectively), the arrival demand is equally distributed to the two runways. If the inner runways are also utilized for arrivals, the percent of demand distributed over the inner runways is the same. However, the magnitude should be much smaller. Thus, the linear function of λ is shown by equation 8 below.

$$\lambda = \sum_{i=1}^{6} \left((inside = 0) \times \beta_{i0} \times arrdemand + (inside = 1) \times \beta_{i1} \times arrdemand \right) \qquad (8)$$

The linear function of λ (average arrival rate) is expressed by the two logical expressions $(inside = 0)$ and $(inside = 1)$, indicating the characteristics of each runway, and by the corresponding arrival demand, *arrdemand*.

4.2. Regression Results

Results show that under VMC meteorological conditions and a base runway configuration, the target LTI for a large-large aircraft pair is 82.26 seconds (Table 5). Table 6 presents target LTIs for aircraft pairs with different fleet mix combinations[4]. Regression results also show that for similar runway configurations but the opposite directions, the target LTIs increases 5.92 seconds. For the same runway configuration, the target LTI for a large-large aircraft pair increases 3.63 seconds under marginal VMC condition, but only 2.38 seconds under IMC condition. Although this finding is somehow counterintuitive, we postulate that a headway separation increased as a result of the air traffic controllers conservative control due to the marginal VMC conditions, while being in the transitioning meteorological condition (between the VMC and the IMC conditions). We propose to further investigate the underlying causes of this intriguing finding.

Table 5 Regression Result of LTI at LAX

Parameter	Interpretation	Estimate	SD	t-stat	P-value
A	Intercept for D	82.26	1.69	48.70	[.000]
γ_1	MVMC	3.63	0.39	9.31	[.000]
γ_2	IMC	2.38	0.44	5.44	[.000]
Ω_2	Runway Configuration 2	-1.72	1.68	-1.02	[.306]
Ω_3	Runway Configuration 3	-4.44	1.69	-2.62	[.009]
Ω_4	Runway Configuration 4	5.92	2.23	2.65	[.008]
Ω_5	Runway Configuration 5	6.70	1.69	3.96	[.000]
Ω_6	Runway Configuration 6	16.03	2.70	5.94	[.000]
t_H	Trailing flight H	-3.98	0.35	-11.39	[.000]
t_S	Trailing flight S	2.68	0.35	7.69	[.000]
l_H	Leading flight H	22.03	0.28	78.14	[.000]
l_S	Leading flight S	-5.43	0.40	-13.68	[.000]
Σ	Controller imprecision	16.66	0.08	202.16	[.000]
β_1	Demand coefficient for runway configuration 1 and 4	3.61E-03	1.80E-04	20.11	[.000]
β_2	Demand coefficient for runway configuration 2 and 5	3.15E-03	2.12E-05	148.74	[.000]
β_3	Demand coefficient for outside runways with configuration 3 and 6	3.05E-03	2.66E-05	114.85	[.000]
β_4	Demand coefficient for inside runways with configuration 3 and 6	1.23E-03	6.28E-05	19.52	[.000]

[4] B757 was taken as a Heavy aircraft when it is leading and a Large aircraft when it is trailing

Capacity is calculated as the inverse of the target LTI. With the estimated results and fleet mix percentages obtained from historical data (Table 6), hourly arrival capacity for a runway dedicated to arrivals with runway configuration 24R, 25L | 24L, 25R at LAX is about 41 operations per hour under VMC condition, as indicated in Table 7.

Table 6. Target Separations and Percentages for Aircraft Pairs under VMC and Runway Configuration 24R, 25L | 24L 25R at LAX

Trailing / Leading	**Target separation**				**Percentage of aircraft pairs**		
	Large	Heavy	Small		Large	Heavy	Small
Large	80	76	82		0.16	0.04	0.04
Heavy	101	97	103		0.28	0.06	0.08
Small	74	70	76		0.23	0.04	0.07

Estimations of hourly capacity of each runway dedicated to arrivals within different runway configurations are presented in Table 7. Capacities are estimated for the same operating conditions indicated in Table 6 (percentage of aircraft pairs and VMC conditions).

Table 7 LAX Capacity for Six Runway Configurations

No.	Runway Configurations		Arrival Capacity
	Landing Runways	Takeoff Runways	(ops. per hour)
1	24R, 25L	24L, 25R	41.02
2	24L, 24R	25L, 25R	42.81
3	24L, 24R, 25L, 25R	24L, 24R, 25L, 25R	43.26
4	6L, 7R	6R, 7L	38.39
5	6L, 6R	7L, 7R	38.07
6	6L, 6R, 7L, 7R	6L, 6R, 7L, 7R	34.60

5. CONCLUSIONS AND FUTURE WORK

This study develops a methodology for assessing airport performance and establishing airport efficiency metrics for runway and airport utilization. The proposed methodology should assist the FAA System Capacity Office in improving measurement and analysis of airport performance. Furthermore, if integrated into ATAC's PDARS tool, the proposed methodology would improve estimation of airport performance and could be automated for daily reporting.

In this study, a normal-lognormal probability distribution for landing time intervals is introduced and compared to the existing four probability distributions. Each probability model is able to capture the overall shape of the observed distribution, although the models for SFO exhibit more variation. However, with the exception of

LAX, the sharp shoulder occurring on the right side of the Controlled-Normal and Normal-Lognormal models do not exist for the other four major airports. For LAX, there is a slight shoulder seen at a landing time interval of approximately 150 seconds. In addition, the Controlled-Normal and Normal-Lognormal models have slightly larger maximum log-likelihood values when compared to the Vandevenne model. These slight differences imply that each airport has a unique probability distribution for arrivals, depending on the number and complexity of runway layouts and runway configurations in use, weather conditions, traffic demand, aircraft mix or air traffic control "culture" deployed at an airport.

Considering the physical meaning of parameters in Vendevenne model, we propose a single-effect model, as a refined Vendevenne model, with linear functions of major parameters (the target separation and the arrival rate). With the results of the regression analysis, hourly capacity of a runway dedicated to arrivals is calculated with a historical fleet mix for different runway configurations. Capacity variation among different runway configurations indicates that more attention should be paid to runway configurations in the capacity study.

We propose to further explore the dynamic behavior of an airport system by investigating transitions of airport runway configurations. It would be interesting to analyze the duration and operational performance of each runway configuration and its transition probabilities to a subsequent configuration by using a semi-Markov process.
Such a study would provide helpful information to the airport system analyst about the nature of runway configuration patterns throughout a desired period of time (day, week, month, or year). It would also be useful in predicting airport states (i.e., runway configurations) and expected airport performance as a function of procedural elements. Because each runway configuration yields a certain level of capacity and delay, the information could be used for improving demand management strategies (on a semi-strategic level), or in making appropriate tactical decisions with the objective to meet the required demand and reduce delays. Furthermore, better predictability of runway configuration patterns and their related operational performance could be useful in determining an appropriate level of automation required during more critical runway-configuration scenarios.

ACKNOWLEDGMENT

The research underlying this paper was conducted by the National Center of Excellence for Aviation Operations Research (NEXTOR). The opinions expressed in this paper are those of the authors, and responsibility for all errors remains with them.

The authors wish to express their gratitude to the Federal Aviation Administration (FAA), and to Paula Lewis, Director of Operations Planning Performance Analysis of Air Traffic Organization, for the financial support. Special thanks to Richard Nehl (Operations Planning Performance Analysis) and Dr. Jady Handal (NAS Quality Assurance and Performance Division) for providing PDARS data. We would also like to thank Mike Keneary of ATAC Corporation for his useful suggestions.

REFERENCES

1. Humphreys I. and Francis G., "Performance Measurement: A review of Airport", International Journal of Transport Management, Volume 1, Number 2, October 2002, pp. 79-85(7)
2. Rakas J., and Yin H, "Statistical Modeling and Analysis of Landing Time Intervals: Case Study of Los Angeles International Airport, California", Transportation Research Record 1915, Washington D.C. 2005, pp. 69-78
3. Vandevenne H.F. and Lippert M.A., "Using Maximum Likelihood Estimation to Determine Statistical Model Parameters for Landing Time Separations", ATC Project Memorandum No. 92PM-AATT-0006, March 17, 2000
4. 2002 Aviation Capacity Enhancement, Office of System Capacity, Plan http://www.faa.gov/ats/asc/02ACE.html, accessed April 24, 2006
5. Airport Capacity Benchmark Report 2001, Federal Aviation Administration, http://www.faa.gov/events/benchmarks, accessed April 24, 2006