Role of Freight Transportation Services and Reduction of Delayed Flights on Productivity of US Airports

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ABSTRACT

Annually million tons of freight and mail are being transported through US airports. The air freight transportation services reportedly result in millions of jobs, activities and dollars which in effect stimulate economic development of regions and the nation as a whole. Beyond passengers and aircraft movements, freight volume nowadays is another major target of opportunity for an airport manager to expand the airport's revenue base and its productivity. This paper analyzes the contribution of freight transportation on airport productivity. The paper also takes into consideration an undesirable output from airport operation i.e., number of delayed flights. As a result, the evaluation of airport productivity should be more comprehensive and fairer in the sense that it regards quantity as well as crediting quality of outputs. High efficiency can be accomplished by increasing desirable outputs and/or decreasing undesirable outputs simultaneously. This characteristic limits the applicability of the traditional Data Envelopment Analysis (DEA) model. This study uses a directional output distance function approach. We applied the approach to assess productivity of 56 US airports operating during 2000 – 2003. The results indicate that freight movements and reduction of delayed flights do contribute to more efficient use of many airports. US airports are actually being operated more efficiently than one might think otherwise.

INTRODUCTION

Besides passengers and movement of aircrafts, freight transportation service is another target market in which an airport manager may be interested. There were more than 23 million tons of freight and mail transported through US airports during 2003. Recently, Bureau of Transportation Statistics (BTS) released a report that John F. Kennedy International airport (JFK) was the top international freight gateway by value in 2004 (*1*). Freight services have increasingly become an important target of opportunity for airport management. They generates job opportunities and more revenue to an airport.

Unlike previous airport productivity studies in the US, this paper will consider both desirable (good) and undesirable (bad) outputs while assessing the productivity of an airport. Due to the nature of airport operations, some desirable outputs are always produced, notably delay and noise. As shown in Figure 1, when passengers increase, we should expect to see higher number of delayed flights. The externalities are a major concern in aviation industry. Taking the undesirable outputs into consideration is therefore making a perfect sense. Such inclusion will lead to meaningful and practical results. The paper will analyze the effect of considering reduction of delays on airport productivity. In addition, the paper aims to show that the provision of freight transportation services may improve productivity of an airport significantly as well.

LITERATURE REVIEW

There is a good number of airport productivity studies carried out around the world (*2* - *13*). These studies typically model an airport as a decision making unit (DMU) taking multiple inputs and producing multiple outputs. Inputs may include production factors such as land area, runway, terminal area, operating expense, and labor units. Major outputs are passengers, aircraft movements and cargo throughput. We observe from previous studies that the results tend to identify busy airports as efficient. Frequently, these efficient airports signal congestion. This is mainly because the chosen set of outputs overemphasizes on quantity of traffic, but none on its quality. Therefore it should be no surprise. Such results may never be acceptable in practice. As we know, there are always externalities from accommodating very high traffic volume, notably delay and noise. They are also outputs from production, though undesirable (bad). Perhaps, we should not ignore the downside of facilities and give credit to airports that keep delays at low levels. The results may become more meaningful, yet practical for the industry.

Although Data Envelopment Analysis (DEA) seems to be a prevailing technique for analyzing productivity of airports (*2 – 12*), it may not be fully applicable where there is joint production of desirable and undesirable outputs (*14 – 17*). The reason lies in its mathematical mechanism in determining whether an airport is on the efficient frontier. For output-oriented DEA models, they would typically seek to maximize the expansion of both types of outputs, rather than expand only the desirable and contract the undesirable. In reality, an airport manager never wishes to expand both number of passengers and delay simultaneously. To account for joint production characteristic, we resort to the directional output distance function which will be described next. To the best of the authors' knowledge, this approach has been applied to study airport productivity only once (*13*). In that study, the author considered aircraft noise (in 1000 New Taiwan dollars) as lone undesirable output.

DIRECTIONAL OUTPUT DISTANCE FUNCTION

Let $y \in R_M^+$ denote a vector of desirable outputs, $b \in R_J^+$ denote a vector of undesirable outputs, and $x \in R_N^+$ denote a vector of inputs. In our context, we examine production of K airports with (x^k, y^k, b^k). We define the production possibility set as the set of desirable and undesirable outputs that can be produced from a given level of inputs which is represented by:

$$P(x) = \{(y,b) : x \text{ can produce } (y,b)\} \quad (1)$$

We assume the following fairly general conditions:

- Null-jointness: If $(y,b) \in P(x)$, and $b = 0$, then $y = 0$. In other words, if an output vector (y,b) is feasible and there are no undesirable outputs produced, then under the null jointness only zero desirable output can be produced. Equivalently, if some positive amount of the desirable output is produced then undesirable output must also be produced.
- Weak disposability between desirable and undesirable outputs: If $(y,b) \in P(x)$ and $0 \le \theta \le 1$, then $(\theta y, \theta b) \in P(x)$. This assumption implies that if undesirables are to be decreased then the desirable outputs must also be decreased, holding inputs x constant. In other words, both desirable and undesirable outputs may be proportionally contracted, but undesirable outputs cannot, in general, be freely disposed. It models the idea that there is a cost to 'cleaning up' undesirable outputs.
- Strong disposability of desirable outputs and of inputs: If $(y,b) \in P(x)$ then for $y' \le y, (y',b) \in P(x)$, and for $x' \ge x, (y',b) \in P(x) \subseteq P(x')$. Strong disposability of desirable outputs implies that it is possible to freely dispose of desirable outputs and

still remain in $P(x)$. Strong disposability of inputs implies that an increase in any one input does not reduce the size of $P(x)$.

- $P(x)$ is convex and compact and the condition of no free lunch is satisfied. That says $P(0) = (0,0)$.

Based on the above assumptions, we can construct the production technology for an individual airport, represented by the following output set:

$$P(x^k) = \{(y,b): \tag{2}$$

$$\sum_{k\in K} \lambda_k y_{km} \geq y_{km}, m = 1,..........., M,$$
$$\sum_{k\in K} \lambda_k b_{kj} = b_{kj}, j = 1,............, J,$$
$$\sum_{k\in K} \lambda_k x_{kn} \leq x_{kn}, n = 1,.............., N,$$
$$\lambda_k \geq 0, k = 1,.........., K\}$$

In Figure 1 we construct $P(x)$ from four hypothetic airports i.e., A, B, C, and D. These airports are assumed to use the same amount of inputs, x, but produce different amounts of desirable output, y, and the undesirable output, b. Since we will make use of linear programming methods to estimate efficiency, $P(x)$ is drawn as piecewise linear. The production possibility set $P(x)$, is bounded by 0ABCD. Airports A, B, C, and D form an efficient frontier.

This figure illustrates how the assumptions are used in the construct. The origin is included in $P(x)$ because of the null-jointness assumption. The assumption of weak disposability implies that for any point on, or inside $P(x)$, a proportional contraction in both (y,b) is feasible. The vertical line segment CD occurs because of strong disposability between desirable outputs. The negative slope portion BC is possible because sometimes traffic may be blocked due to long queue of delayed flights; hence reducing throughput. Note that if we ignore undesirable outputs, then $P(x)$ will be the area bounded by 0GBCD.

Next we are interested in estimating the level of inefficiency for all airports. In other words, we want to know how far each airport is from the efficient frontier. Let's say we are about to check how far away is airport E from the frontier along the diagonal line EJ or in the direction of vector $g = (g_y, -g_b)$. This measurement is justified on the premise that we seek to maximize the expansion of desirable outputs and contraction of undesirable outputs simultaneously. The directional output distance function is then formulated as follows:

$$\vec{D}_0(x, y, b; g_y, -g_b) = \max\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\} \tag{3}$$

To assess the level of inefficiency for individual airports, we then solve the following linear programming problem:

$$
\begin{aligned}
&\max \beta \\
&s.t. \\
&\sum_{k \in K} \lambda_k y_{km} \geq y_{km} + \beta g_y, m = 1, \ldots\ldots\ldots, M, \\
&\sum_{k \in K} \lambda_k b_{kj} = b_{kj} - \beta g_b, j = 1, \ldots\ldots\ldots\ldots, J, \\
&\sum_{k \in K} \lambda_k x_{kn} \leq x_{kn}, n = 1, \ldots\ldots\ldots\ldots\ldots, N, \\
&\lambda_k \geq 0, k = 1, \ldots\ldots\ldots, K\}
\end{aligned}
\tag{4}
$$

The directional output distance function $\vec{D}_0(x, y, b; g_y, -g_b)$ or an optimal β takes the minimum value of zero when it is not possible to expand the desirable outputs and contract undesirable outputs. This means that the airport is efficiently producing at the maximum possible outputs. A higher value of β indicates a higher level of inefficiency. Selection of directional vector $g = (g_y, -g_b)$ is rather flexible. For example, using $g = (0, b)$ means that we are about to measure the level of inefficiency along the horizontal line EI or projected to the frontier at H. Meanwhile, using $g = (y, 0)$ yields the projection on the frontier at K. Using $g = (1, -1)$ gives the same weight to both inputs and outputs. In this study, we will use $g = (y, -b)$ which means that the projected direction is depending on individual airport's outputs.

DATA

We chose to analyze role of freight transportation services and reduction of delayed flights on productivity of US airports. For convenience, we take part of the samples from our previous airport productivity study (*12*) and collect additional samples to expand the size of samples. Overall, there are 56 airports from all over the US. This sample size is larger than most previous studies (*2 – 11*, *13*). A recent 4-year panel data during 2000 - 2003 is used in the analysis which allows us to observe the productivity trend over time.

The linear programming in (4) requires data on vectors of inputs, and desirable and undesirable outputs (x^k, y^k, b^k) of individual airports. Chosen inputs and outputs largely depend upon the focus of the analysis. Often times, one is not completely free to choose any, but rather bounded by the availability of data across sampled airports. Therefore, the general ideal is trying to consider common, yet comprehensive set of inputs and outputs so that the results are meaningfully practical.

There are three common physical inputs that we consider in this study i.e., land area, number of runways and runway area. Runway area is the summation of product between length and width of all existing runways, whether it is being in use or not. We intentionally include runway area to capture the effect of design configuration such as length, width, separation, and orientation. This should provide more meaningful results than having the number of runways alone. For the set of desirable outputs, it is assumed that airport managers aim at producing passengers, non-delayed flights and cargo throughput. The airport operation produces also externalities in the form of two undesirable outputs i.e., delayed flights and time delay.

We started to collect inputs data from the Airport Master Record database (*21*). The database is rather up-to-date; for many airports they were surveyed after 2003. Therefore, we need to check if there was any change during the period. After verification with airport websites, airport managers, and reports; it can be concluded that most airports did not have significant improvement during the study period. The chosen airports have been well established and have been serving the market for years. This should relieve concerns about sudden efficiency drop during the early years after lumpy investment. We may assume with caution that any temporal change in productivity that might be observed, is a result from operational performance. However, there were major changes in runway characteristics at some airports. For example, Detroit Metropolitan Wayne County (DTW) opened its 6th runway on December 11, 2001. Its number of runways is edited accordingly. Number of runway and runway acreage are computed precisely by the time it is in service during the year, rounding down in month. As a result, DTW had 5 and 6 runways in 2001 and 2002 respectively.

Annual statistics on number of passengers, cargo throughput, and aircraft movements (regardless of delayed or non-delayed flights) are published regularly by the Airports Council International (*18 – 20*). Number of delayed flights and total time delays can be queried from FAA database (*22*). According to FAA definition, a flight is counted as a delayed flight when it deviates from its schedule more than 15 minutes. Time delayed is accumulated from the 15th minute deviation till its landing.

Table 1 lists all 56 airports along with ICAO airport codes and their corresponding outputs in 2003. The airports are ordered by number of annual passengers. On the top of the list, Hartsfield-Jackson Atlanta (ATL) is actually the busiest airport of the world in term of passengers. O'Hare (ORD) serviced the highest movements. Memphis International (MEM), the FedEx hub, had the highest cargo throughput. On the down side, ORD experienced the highest delayed flights. Descriptive statistics on inputs and outputs are summarized in Table 2. The number of non-delayed flights is the difference between aircraft movements and number of delayed flights. During the study period, all airports experienced delay for at least one flight, as shown by the minimum statistics. Large standard deviations suggest that sampled airports are different in both scale and scope of operations.

RESULTS AND DISCUSSION

We set up data into three cases. The directional output distance function in (4) is then applied to each case. All cases have the same set of inputs, but different sets of outputs. Specifications of the data sets and case purposes are as follows:

Case 1: This case is used as a base case for comparison.

- Set of inputs = {land area, number of runways, runway area}
- Set of desirable outputs = {passengers, aircraft movements}
- Set of undesirable outputs = { Φ }

Case 2: This case adds cargo throughput into the set of desirable outputs. The difference in efficiency score β between Case 1 and 2 is the contribution of freight transportation on productivity of airports.

- Set of inputs = {land area, number of runways, runway area}
- Set of desirable outputs = {passengers, aircraft movements, cargo throughput}
- Set of undesirable outputs = { Φ }

Case 3: This case separates aircraft movements into non-delayed and delayed flights. Non-delayed flight is put in the set of desirable outputs. Delayed flight is included in the set of undesirable outputs. The difference between case 3 and 1 is the contribution of freight transportation and delayed flights on productivity of airports.

- Set of inputs = {land area, number of runways, runway area}
- Set of desirable outputs = {passengers, non-delayed flights, cargo throughput}
- Set of undesirable outputs = {delayed flights}

For each case, we solved the linear program (4) a total of 56 times for individual airports to determine β. An optimal β or distance from the efficient frontier measures level of inefficiency. An efficient airport has $\beta = 0$. A higher value of β indicates a higher level of inefficiency. Table 3 shows efficiency score for each case in each year 2000 – 2003.

Clearly, freight service does affect the efficiency measure of airports. Comparing between cases 1 and 2, freight services in term of cargo throughput; make many airports more efficient. For example in year 2003, case 2 identified six efficient airports whereas case 1 did just four (two fewer). One might argue that it is always true that inclusion of more factors would likely identify more efficient airports. However, the inclusion needs to be justified. Such factors should be logical and meaningful in practice. From results in case 1, if cargo throughput is not considered as an output, then Memphis International (MEM) is not regarded as efficient although it is the busiest airport of the world in term of freight services. It is rather evident that cargo throughput should be a major factor in studying the productivity of US airports. In general, inclusion of cargo throughput, better the overall efficiency of the whole system, as the summation and average efficiency scores are lower than in the case 1.

One might observe that efficient airports are very busy airports. For example, Hartsfield-Jackson Atlanta (ATL) and Memphis International (MEM) are indeed two busiest airports in the world from passengers and cargo throughput respectively. LaGuardia (LGA) has been under control for years. John Wayne airport (SNA) constrains the number of passengers. This is rather typical results in airport productivity studies whenever the set of outputs emphasizes on quantity, but not quality. The implication is that an airport needs to be very busy in order to be regarded as efficient. Many airport managers may be reluctant to buy such suggestion.

The results identified more efficient airports when an undesirable output i.e., the number of delayed flights is taken into consideration. Again, inclusion of delays makes perfect sense in practice. Customers of airport (e.g., passengers, airlines, and shippers), airport operators, FAA (regulator) do concern about delays. All stakeholders want to minimize delay. Therefore, a practical analysis should not give credit only to airports that produce more outputs but also to the ones that reduce delays. Results in Table 3 show that many more airports are in fact operated rather efficiently. In 2003, 19 airports are identified as efficient or 13 more airports as compared with case 2. Evidently, taking reduction of delayed flights into account, the US aviation system is actually being operated quite efficiently.

In order to prove that efficiency scores are significantly different among cases, we applied several statistical tests to the results. Table 4 shows results from paired sample t-tests which strongly support the assertion. To avoid restricted assumptions of t-tests, the non-parametric Wilcoxon signed-rank test and sign test are also performed. The results are shown in Table 5 and 6 respectively. They confirm that the difference in efficiency scores between cases is significant. To test the difference among three cases simultaneously, two non-parametric tests for several related samples are performed. Again, both Friedman and Kendall's W tests confirm the difference in efficiency scores across cases, as shown in Table 7.

Note that the lumpiness of runway investment really signifies the efficiency drop in the early years, as the results indicate in the case of DTW. During 2000 – 2001, its efficiency score was rather stable, but downgraded significantly in 2002 and 2003. One should always be cautious when interpreting efficiency score change in this case. In general, it is unlikely to see dramatic efficiency change at well-established airports. Once it occurs, it should be investigated carefully.

CONCLUSIONS

This paper analyzed the role of freight transportation services and reduction of delayed flights on productivity of airports. Since the traditional Data Envelopment Analysis (DEA) has a limitation to deal with undesirable outputs when assessing efficiency, the directional output distance function is instead adopted. The approach is applied to a recent panel data 2000 – 2003 of 56 US airports. The results indicate that provision of freight transportation services, as represented by cargo throughput; do improve the efficiency of an airport and airport system as a whole. Furthermore, when reduction in delays is considered as well, it becomes clearer that US airports actually are being operated rather efficiently. We proved the significance of the efficiency improvement by using several parametric and non-parametric statistical tests. It is also noted that in cases where there is a major new investment we should expect an efficiency drop during the early years after the construction.

We conclude that an airport productivity study should consider cargo throughput and delays as major outputs of an airport. Generally, both desirable and undesirable outputs should be considered in tandem. This will give more meaningful and practical results.

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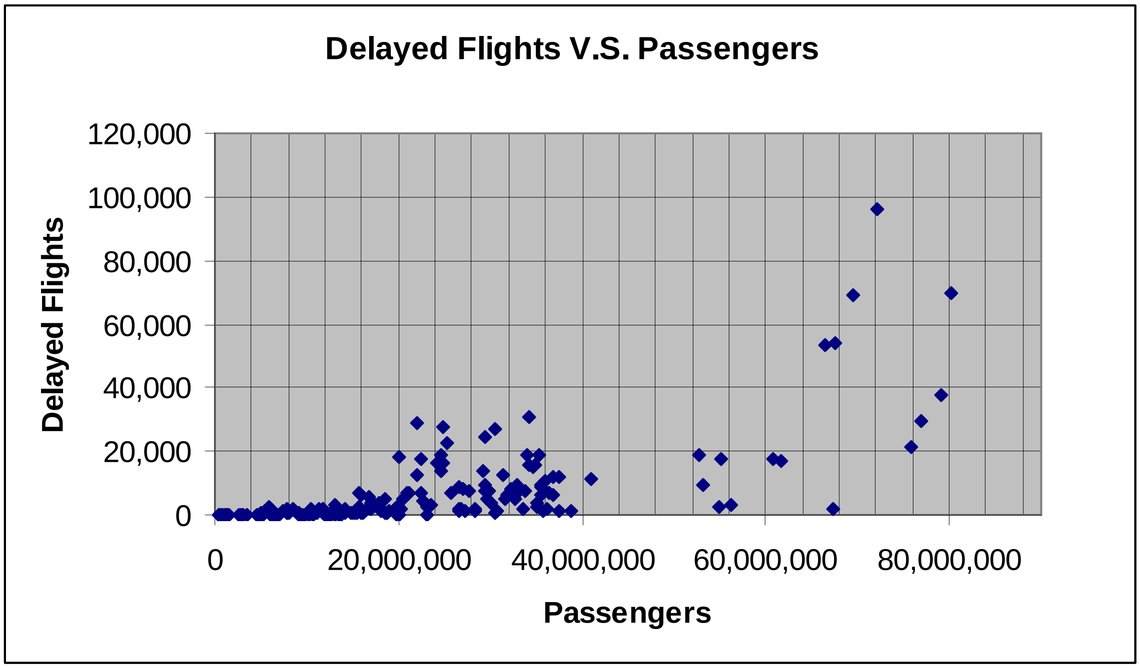

FIGURE 1 Scatter Plot between Number of Delayed Flights and Number of Passengers

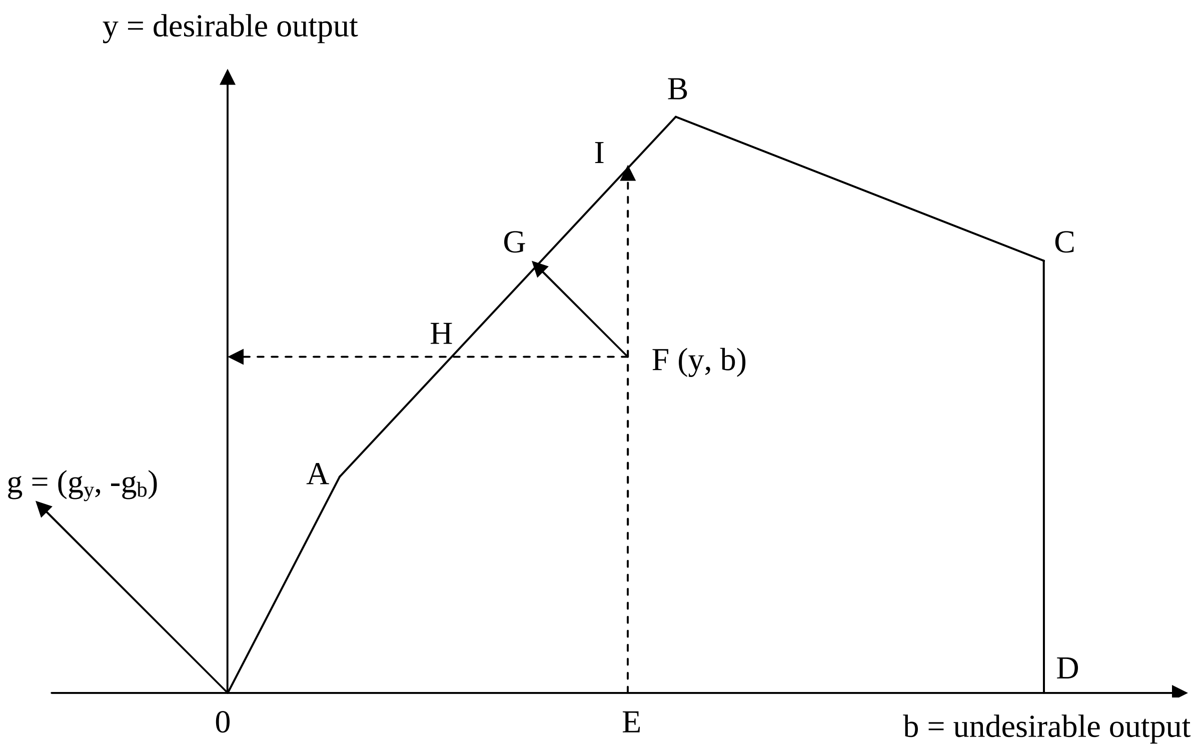

FIGURE 2 Graphical Illustration of Directional Output Distance Function Concept

TABLE 1 List of 56 US Airports under Consideration and their Outputs in 2003

	Airport Name	Airport Code	Total Passengers	Cargo (ton)	Aircraft Movements	Non Delayed Flights	Delayed Flights
1	Hartsfield-Jackson Atlanta International	ATL	79,086,792	798,501	911,723	874,203	37,520
2	O'Hare International	ORD	69,508,672	1,510,746	928,691	859,506	69,185
3	Los Angeles International, CA	LAX	54,982,838	1,833,300	622,378	620,178	2,200
4	Dallas/Fort Worth International, TX	DFW	53,253,607	667,574	765,296	755,873	9,423
5	Denver International, CO	DEN	37,505,138	325,350	499,794	498,469	1,325
6	Phoenix Sky Harbor International, AZ	PHX	37,412,165	288,350	541,771	529,971	11,800
7	McCarran International, NV	LAS	36,285,932	82,153	501,029	494,332	6,697
8	George Bush Intercontinental, TX	IAH	34,154,574	381,926	474,913	458,924	15,989
9	Minneapolis/St. Paul International, MN	MSP	33,201,860	315,987	510,382	503,049	7,333
10	Detroit Metropolitan Wayne County, MI	DTW	32,664,620	220,246	491,073	486,231	4,842
11	John F. Kennedy International, NY	JFK	31,732,371	1,626,722	280,302	274,217	6,085
12	Miami International, FL	MIA	29,595,618	1,637,278	417,423	412,559	4,864
13	Newark Liberty International, NJ	EWR	29,431,061	874,641	405,808	381,159	24,649
14	San Francisco International, CA	SFO	29,313,271	573,523	334,515	325,205	9,310
15	Orlando International, FL	MCO	27,319,223	193,037	295,542	294,300	1,242
16	Seattle Tacoma International, WA	SEA	26,755,888	351,418	354,770	352,786	1,984
17	Philadelphia International, PA	PHL	24,671,075	524,485	446,529	432,902	13,627
18	Charlotte/Douglas International, NC	CLT	23,062,570	140,085	443,394	440,079	3,315
19	Boston Logan International, MA	BOS	22,791,169	363,082	373,304	369,452	3,852
20	LaGuardia, NY	LGA	22,482,770	28,402	374,952	357,054	17,898
21	Covington/Cincinnati/Northern Kentucky International, KY	CVG	21,228,402	392,695	505,557	498,577	6,980
22	Lambert-St. Louis International, MO	STL	20,427,317	115,574	379,772	374,984	4,788
23	Baltimore/Washington International, MD	BWI	20,094,756	235,576	299,469	297,733	1,736
24	Honolulu International, HI	HNL	19,732,556	421,930	319,989	319,976	13
25	Salt Lake City International, UT	SLC	18,466,756	216,870	400,452	399,680	772
26	Midway International, IL	MDW	18,426,397	23,266	328,035	323,041	4,994
27	Fort Lauderdale - Hollywood International, FL	FLL	17,938,046	156,449	287,593	283,700	3,893
28	Washington Dulles International, VA	IAD	16,767,767	285,352	335,397	329,552	5,845
29	Tampa International, FL	TPA	15,523,568	93,457	233,601	232,471	1,130
30	San Diego International, CA	SAN	15,260,791	135,547	203,285	202,506	779

	Airport Name	Airport Code	Total Passengers	Cargo (ton)	Aircraft Movements	Non Delayed Flights	Delayed Flights
31	Pittsburg International, PA	PIT	14,266,984	121,536	361,329	360,619	710
32	Ronald Reagan Washington National, DC	DCA	14,214,803	5,774	250,802	249,056	1,746
33	Oakland International, CA	OAK	13,548,363	597,383	342,871	342,567	304
34	Portland International, OR	PDX	12,395,938	239,265	267,052	266,872	180
35	Memphis International, TN	MEM	11,437,307	3,390,515	402,258	400,683	1,575
36	Mineta San Jose International, CA	SJC	10,677,903	108,622	198,082	197,855	227
37	Cleveland Hopkins International, OH	CLE	10,555,387	95,761	258,460	256,993	1,467
38	Kansas City International, MO	MCI	9,715,411	136,687	170,758	170,722	36
39	Louis Armstrong New Orleans International, LA	MSY	9,275,690	80,831	137,312	137,094	218
40	John Wayne, CA	SNA	8,535,130	12,050	350,074	348,475	1,599
41	William P. Hobby, TX	HOU	7,803,330	5,775	242,635	242,084	551
42	Ontario International, CA	ONT	6,547,877	518,710	146,413	146,212	201
43	Port Columbus International, OH	CMH	6,252,061	10,766	237,979	237,915	64
44	Albuquerque International Sunport Airport, NM	ABQ	6,051,879	71,599	221,003	220,962	41
45	Palm Beach International, FL	PBI	6,010,820	18,300	171,692	169,836	1,856
46	Jacksonville International, FL	JAX	4,883,329	70,650	121,143	121,043	100
47	Anchorage International, AK	ANC	4,791,431	2,102,025	277,361	277,165	196
48	Bob Hope, CA	BUR	4,729,936	44,654	178,079	177,902	177
49	Norfolk International, VA	ORF	3,436,391	32,283	121,373	121,330	43
50	Long Beach, CA	LGB	2,875,703	50,873	338,807	338,727	80
51	Birmingham International, AL	BHM	2,672,637	34,184	154,849	154,781	68
52	Pensacola Regional, FL	PNS	1,361,758	4,569	127,197	127,195	2
53	Palm Spring International, CA	PSP	1,246,842	103	93,068	93,032	36
54	Jackson International,	JAN	1,215,093	10,957	79,377	79,376	1
55	Santa Barbara, CA	SBA	752,762	2,825	152,485	152,434	51
56	Stewart International, NY	SWF	393,530	19,024	112,284	112,277	7
	Total		1,094,725,865	22,599,243	18,781,482	18,485,876	295,606

TABLE 2 Descriptive Statistics of Samples 2000 – 2003

Statistics	Inputs			Desirable Outputs			Undesirable Output
	Land area (acre)	Number of runways	Runway area (acre)	Total passengers	Cargo throughput (ton)	Non delayed flights	Delayed flights
Minimum	501	1.00	24.60	362,017	74	79,376	1
Maximum	33,422	7.00	305.87	80,162,407	3,390,800	874,203	96,346
Range	32,921	6.00	281.26	79,800,390	3,390,726	794,827	96,345
Mean	4,381	3.35	104.21	20,009,558	401,667	343,324	5,818
Median	2,650	3.00	99.56	16,225,655	171,349	326,086	1,355
Standard deviation	5,298	1.21	51.65	16,924,416	591,702	176,881	11,917

TABLE 3 Efficiency Scores for Three Cases

Airport Code	2000			2001			2002			2003		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
ABQ	2.651	2.603	0.474	2.328	2.328	**0.000**	2.139	2.139	0.060	2.566	2.566	0.173
ANC	1.676	0.231	**0.000**	1.348	0.051	0.051	1.407	0.272	**0.000**	1.465	0.161	**0.000**
ATL	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
BHM	2.049	2.049	0.395	1.821	1.821	0.326	1.842	1.842	0.529	1.706	1.706	0.273
BOS	1.103	0.950	0.677	1.148	1.013	0.708	1.438	1.114	0.601	1.594	1.199	0.557
BUR	1.446	1.415	0.060	1.405	1.368	**0.000**	1.313	1.252	0.000	1.051	0.967	**0.000**
BWI	1.876	1.800	0.672	1.627	1.609	0.282	1.772	1.691	0.375	1.839	1.788	0.443
CLE	1.519	1.489	0.512	1.728	1.728	0.490	2.112	2.101	0.707	1.992	1.945	0.578
CLT	0.610	0.610	0.363	0.406	0.406	0.142	0.416	0.416	0.306	0.472	0.472	0.294
CMH	1.070	1.070	**0.000**	0.795	0.795	**0.000**	0.701	0.701	**0.000**	0.856	0.856	**0.000**
CVG	0.618	0.550	0.420	0.724	0.724	0.421	0.372	0.372	0.252	0.353	0.353	0.170
DCA	0.761	0.761	0.227	0.967	0.967	0.446	1.071	1.071	0.297	0.896	0.896	0.302
DEN	1.291	1.238	0.327	1.280	1.280	0.063	1.226	1.226	0.091	1.432	1.432	0.129
DFW	1.048	0.972	0.759	0.989	0.946	0.667	1.036	1.019	0.784	1.085	1.085	0.590
DTW	1.299	1.299	0.714	1.132	1.132	0.622	1.699	1.699	0.716	1.754	1.754	0.632
EWR	0.373	0.089	**0.000**	0.393	0.206	0.133	0.486	0.154	0.063	0.511	0.142	**0.000**
FLL	1.065	0.874	0.673	0.894	0.754	0.159	0.869	0.718	0.359	0.834	0.707	0.365
HNL	1.856	1.691	**0.000**	1.682	1.624	**0.000**	1.707	1.524	**0.000**	1.783	1.590	**0.000**
HOU	2.098	2.098	0.498	2.075	2.075	0.429	2.069	2.069	0.487	2.046	2.046	0.347
IAD	0.694	0.629	0.595	0.683	0.682	0.362	0.791	0.778	0.559	1.039	1.039	0.664
IAH	0.874	0.870	0.518	0.842	0.839	0.461	0.948	0.948	0.621	1.000	1.000	0.623
JAN	4.290	4.290	**0.000**	3.653	3.653	**0.000**	4.156	4.156	0.148	4.436	4.436	**0.000**
JAX	2.276	2.276	0.534	2.222	2.222	0.499	2.457	2.457	0.559	2.609	2.609	0.507
JFK	1.440	0.347	0.324	1.585	0.473	0.310	1.567	0.425	0.417	1.492	0.376	0.373
LAS	0.644	0.644	0.594	0.690	0.690	0.158	0.672	0.672	0.418	0.648	0.648	0.498
LAX	0.024	**0.000**	**0.000**	0.092	**0.000**	**0.000**	0.194	**0.000**	**0.000**	0.252	**0.000**	**0.000**
LGA	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
LGB	1.380	1.196	**0.000**	1.461	1.223	**0.000**	1.448	1.258	**0.000**	1.406	1.228	**0.000**
MCI	2.489	2.407	0.285	2.182	2.182	0.247	2.485	2.485	0.338	2.998	2.998	0.356
MCO	0.927	0.927	0.277	1.014	1.014	**0.000**	1.163	1.163	0.082	1.171	1.171	0.155
MDW	0.336	0.336	0.065	0.288	0.288	**0.000**	0.168	0.166	**0.000**	0.118	0.118	**0.000**

Airport Code	2000			2001			2002			2003		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
MEM	1.127	**0.000**	**0.000**	1.190	**0.000**	**0.000**	1.160	**0.000**	**0.000**	1.172	**0.000**	**0.000**
MIA	0.454	0.030	0.029	0.401	**0.000**	**0.000**	0.477	0.023	**0.000**	0.748	0.165	0.150
MSP	0.352	0.349	0.191	0.295	0.295	0.187	0.275	0.275	0.220	0.288	0.288	0.195
MSY	2.755	2.604	0.200	2.606	2.482	**0.000**	2.754	2.494	**0.000**	2.859	2.604	0.163
OAK	0.918	0.528	**0.000**	1.034	0.546	0.057	1.127	0.651	0.042	1.260	0.731	**0.000**
ONT	2.066	1.212	0.004	1.758	1.200	0.259	1.852	1.055	**0.000**	1.917	1.036	0.114
ORD	0.755	0.531	0.532	0.674	0.496	0.499	0.649	0.465	0.468	0.669	0.478	0.465
ORF	2.585	2.585	0.295	2.423	2.423	0.437	2.208	2.208	0.287	2.287	2.287	0.253
PBI	2.282	2.282	0.799	2.164	2.164	0.297	2.519	2.519	0.709	2.435	2.435	0.764
PDX	1.309	1.137	**0.000**	1.224	1.165	**0.000**	1.326	1.255	**0.000**	1.439	1.377	0.042
PHL	0.775	0.651	0.718	0.739	0.629	0.613	0.733	0.563	0.584	0.785	0.588	0.609
PHX	**0.000**	**0.000**	**0.000**	0.149	0.149	0.142	0.159	0.159	0.137	0.174	0.174	0.140
PIT	1.297	1.297	0.234	0.971	0.971	0.192	1.094	1.094	0.399	1.523	1.523	0.366
PNS	2.739	2.739	0.172	2.477	2.477	**0.000**	2.050	2.050	0.091	2.091	2.091	**0.000**
PSP	4.061	4.061	0.559	3.716	3.716	0.781	3.567	3.567	**0.000**	3.096	3.096	0.447
SAN	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
SBA	2.488	2.488	**0.000**	2.548	2.548	**0.000**	2.467	2.467	**0.000**	2.455	2.455	**0.000**
SEA	0.147	0.082	**0.000**	0.111	0.087	0.056	0.220	0.182	**0.000**	0.285	0.261	**0.000**
SFO	0.953	0.772	0.648	1.190	0.983	0.622	1.444	1.120	0.780	1.698	1.289	0.782
SJC	1.058	0.867	**0.000**	1.195	0.834	0.315	1.669	1.135	0.323	1.848	1.389	**0.000**
SLC	1.738	1.659	0.711	1.374	1.374	0.218	1.167	1.167	0.160	1.249	1.249	0.227
SNA	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
STL	0.399	0.399	**0.000**	0.321	0.321	0.325	0.425	0.425	0.411	0.636	0.636	0.535
SWF	2.581	2.581	0.025	2.817	2.817	0.152	2.497	2.497	**0.000**	2.904	2.904	0.295
TPA	1.590	1.590	0.514	1.489	1.489	0.128	1.649	1.649	0.170	1.801	1.801	0.401
Sum	74.216	66.154	15.594	70.320	63.258	12.256	73.213	64.908	13.548	77.022	68.143	13.977
Average	1.325	1.181	0.278	1.256	1.130	0.219	1.307	1.159	0.242	1.375	1.217	0.250
# of efficient airports	5	7	19	4	7	19	4	6	19	4	6	19

Note: An efficient airport has a zero score as labeled by bold typeface.

TABLE 4 Comparisons of Efficiency Scores by Paired Sample t-test

Pairs	Paired Differences					t
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		
				Lower	Upper	
Pair 1: Case 1 – Case 2	0.14420	0.294923	0.019705	0.10536	0.18303	7.318
Pair 2 : Case 1 – Case 3	1.06871	0.919862	0.061461	0.94759	1.18982	17.388
Pair 3: Case 2 – Case 3	0.92451	0.951749	0.063591	0.79919	1.04983	14.538

TABLE 5 Comparisons of Efficiency Scores by Wilcoxon Signed-Rank Test

Pair	Z	Asymptotic Significance (2-tailed)
Pair 1: Case 1 – Case 2	-8.768[a]	0.000
Pair 2 : Case 1 – Case 3	-12.474[a]	0.000
Pair 3: Case 2 – Case 3	-12.089[a]	0.000

a. Based on positive ranks.

TABLE 6 Comparisons of Efficiency Scores by Sign Test

Pair	Z	Asymptotic Significance (2-tailed)
Pair 1: Case 1 – Case 2	-10.000	0.000
Pair 2 : Case 1 – Case 3	-14.179	0.000
Pair 3: Case 2 – Case 3	-12.967	0.000

TABLE 7 Comparisons of Efficiency Scores by Non-parametric Tests for Several Related Samples

Friedman Test	
N	224
Chi-Square	352.53
Degree of freedom	2
Asymptotic Significance	0.000
Kendall's W Test	
N	224
Kendall's W[a]	0.787
Chi-Square	352.53
Degree of freedom	2
Asymptotic Significance	0.000

a. Kendall's Coefficient of Concordance