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Airlines Performance via Two-Stage Network DEA Approach

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Abstract

The performance of the airline industry has been widely studied using data envelopment analysis (DEA). Many existing DEA-based airline performance studies have used the standard DEA model, with some minor modifications. These studies have ignored the internal structure relative to the measures characterizing airline operations performance. In the current paper, airline performance is measured using a two-stage process. In the first stage, resources (fuel, salaries, and other factors) are used to maintain the fleet size and load factor. In the second stage, the fleet size and load factors generate revenue. The model used is called the centralized efficiency model where two stages are used to optimize performance simultaneously. The approach generates efficiency decomposition for the two individual stages. The use of this centralized DEA model enables obtaining insights not available from the standard DEA approach.

Keywords: DEA, efficiency, airline, intermediate measure, centralized

JEL Classification code: C02

In a recent article in the *Wall Street Journal*, airlines' fuel efficiency was identified as one of the factors when choosing a flight (McCartney, 2010). The article points out that Alaska is number 1 in fuel economy and flew a seat 76 miles, on average, on a gallon of fuel in 2009. However, more factors are related to the performance of airlines. For example, in evaluating the operational performance of 14 major international passenger carriers in 1990, Schefczyk (1993) considered aircraft capacity, operating costs, non-flight assets, passenger kilometers, and non-passenger revenue. Tofallis (1997) used a modified data envelopment analysis (DEA) approach, namely, input efficiency profiling, to study the same data set.

The DEA has been widely used in studies on airline efficiency and performance benchmarking. Most of the studies suggested high levels of operational efficiency in major airlines, while some DEA studies focused on airport efficiency (cf. Adler & Golany, 2001; Alam, Semenick, & Sickles, 1998; Banker & Johnston, 1994; Charnes, Galleous, & Li, 1996; Gillen & Lall, 1997; Good, Roller, & Sickles, 1995; Scheraga, 2004; Tongzon, 2001). Most recently, Lee and Worthington (2010) determined whether the inclusion of low-cost airlines in a dataset of international and domestic airlines had an impact on the efficiency scores of so-called 'prestigious' and purportedly 'efficient' airlines. All the DEA-based studies cited employ the standard DEA approach with some minor modifications and improvements.

While the DEA studies cited above provide meaningful insights about airlines' operational performance, some recent developments in DEA enable study of the airline industry by examining the 'internal relations' of the factors related to the airline operational performance.

Specifically, in the studies cited above, each airline was treated as a decision-making unit (DMU) in the presence of multiple inputs and outputs. In other words, all the factors related to airline operational performance were classified as inputs or outputs. Yet, in many cases, factors can be classified as either inputs or outputs because they are intermediate measures. For example, Seiford and Zhu (1999) decomposed bank performance into profitability and marketability. In their study, profitability was measured using labor and assets as inputs, and the outputs were profits and revenue. In the marketability stage, the profits and revenue were used as inputs, while market value, returns, and earnings per share were used as outputs. Seiford and Zhu used the standard DEA approach that does not address potential conflicts between the two stages arising from the intermediate measures. For example, the second stage may have to reduce its inputs (intermediate measures) in order to achieve an efficient status. Such an action would imply a reduction in the first stage outputs, thereby reducing the efficiency of that stage. To address the conflict, Kao and Hwang (2008) and Liang, Cook, and Zhu (2008) developed a DEA-based cooperative game approach where efficiency scores for both individual stages and the overall process could be obtained. This new approach assumed both stages' efficiency scores were maximized simultaneously while determining a set of optimal (common) weights assigned to the intermediate measures.

The current study applies the centralized model of Liang, Cook, and Zhu (2008) to a set of 21 airlines. The importance of characterizing internal relations among performance measures is demonstrated. The remainder of the paper is organized as follows: Section 2 presents the data and the model, and the empirical results are presented in Section 3. Conclusions follow in Section 4.

Data and Model

The data for the current study were collected from www.wikinvest.com. Data for 21 airlines were available for 2007 and 2008. Based upon whether data were available for most of the airlines, factors related to airline performance selected were the following: (a) cost per available seat mile; (b) salaries, wages, and benefits per available seat mile; (c) fuel expense per available seat mile; (d) fuel cost; (e) gallons of fuel used; (f) load factor; (g) fleet size; (h) revenue passenger miles; and (i) passenger revenue. Other factors, for example, fuel cost per gallon and revenue per available seat mile, were not selected because these factors are strongly related to the ones selected.

The definitions of the selected factors based upon www.wikinvest.com are presented next. Tables 1 and 2 present the data for 2007 and 2008 respectively. The definitions for the selected factors of performance are defined below.

Cost per available seat mile (CASM) is the amount it costs an airline to fly one seat one mile. CASM is calculated per available seat mile, rather than per passenger mile, because the cost to an airline is essentially the same minus the cost of beverage service and other small items, regardless of whether a passenger fills the seat or not. CASM is the primary measure unit of cost in the airline industry: the lower the CASM, the more efficient the airline is operating and thus, the more likely the airline will be profitable.

Salaries, wages, and benefits per available seat mile shows how efficient an airline's employees are; in other words, the lower the salaries, wages, and benefits per available seat mile, the more efficient the airline's employees are operating.

Fuel expense per available seat mile is calculated by dividing the total fuel expenses by available seat mile. A lower value indicates a more efficient aircraft.

Fuel cost describes how much an airline pays for its jet fuel. Fuel cost represents the largest operating expense for airlines, accounting for 25%-50% of annual operating expenses, depending on the airline. Fuel costs can vary significantly, primarily because some airlines buy futures that help them hedge against rises in oil prices. Because fuel cost is highly volatile, fluctuations in oil prices can significantly affect airlines' financial performance. For example, United's 61% increase in fuel expenses spurred a 29% jump in operating expenses in 2008.

Table 1
Airline Data in 2007

Airline	Cost per available seat mile (ASM)	Salaries, wages, & benefits per ASM	Fuel expense per ASM	Fuel cost (millions)	Gallons of fuel used (million)	Load factor	Fleet size	Revenue passenger miles (billion)	Passenger revenue (million)
AirTran Holdings	0.0957	0.02000	0.0350	804	360	0.762	137	17.3	2200
Allegiant Travel Company	0.0819	0.01310	0.0394	152	66	0.813	32	3.14	294
Alaska Air Group	0.1050	0.03960	0.0362	876	354	0.762	185	18.5	3240
Continental Airlines	0.1080	0.02700	0.0290	3350	1540	0.814	263	94.2	13000
China Eastern Airlines	0.1180	0.01180	0.0413	1990	2.55	0.736	147	35.5	4950
Delta Air Lines Inc.	0.1190	0.02800	0.0310	4690	2120	0.806	578	122.0	16900
Frontier Airlines Holdings	0.0976	0.01420	0.0303	343	141	0.752	66	9.11	1130
Gol Intelligent Airlines Inc.	0.1410	0.02110	0.0502	1070	311	0.660	111	22.7	2580
Hawaiian Holdings Inc	0.1060	0.02410	0.0316	292	130	0.874	29	8.06	889
JetBlue Airways	0.0838	0.02030	0.0291	929	444	0.807	128	25.7	2640
US Airways Group	0.1130	0.03040	0.0347	2630	1200	0.808	356	61.3	10800
Lan Airlines S.A.	0.1590	0.02500	0.0600	930	407	0.761	81	14.9	2200
Southwest Airlines Company	0.0910	0.03220	0.0255	2540	1490	0.726	520	72.3	9460
Mesa Air Group	0.1470	0.00782	0.0477	438	202	0.757	182	6.95	1310
Republic Airways Holdings	0.1020	0.01970	0.0258	297	123	0.745	219	8.58	1270
Ryanair Holdings	0.0722	0.00946	0.0160	921	377	0.760	133	24.9	2510
SkyWest	0.1370	0.03160	0.0462	1060	441	0.779	436	17.9	3340
United Continental Holdings, Inc.	0.1350	0.03000	0.0350	5000	2290	0.827	460	118.0	18300
ExpressJet	0.1320	0.03220	0.0238	323	323	0.742	274	10.1	1650
Northwest Airlines	0.1080	0.02750	0.0362	3380	1720	0.839	356	78.3	9430
AMR CORP	0.1140	0.04000	0.0400	6670	3130	0.815	655	138.0	20700

Table 2
Airline Data in 2008

Airline	Cost per available seat mile (ASM)	Salaries, wages, & benefits per ASM	Fuel expense per ASM	Fuel cost (million)	Gallons of fuel used (million)	Load factor	Fleet size	Revenue passenger miles (billion)	Passenger revenue (million)
AirTran Holdings	0.1100	0.0199	0.0502	1190	368	0.796	136	19	2410
Allegiant Travel Company	0.1010	0.0162	0.0517	230	77	0.870	38	3.86	383
Alaska Air Group	0.1250	0.0390	0.0480	1160	334	0.773	110	18.7	2640
Delta Air Lines Inc.	0.1870	0.0290	0.0443	7350	2740	0.814	1020	135	1960
Frontier Airlines Holdings	0.1030	0.0142	0.0353	447	162	0.796	70	11	1350
Hawaiian Holdings Inc	0.1180	0.0256	0.0300	425	134	0.827	33	7.84	1110
JetBlue Airways	0.1010	0.0214	0.0417	1350	453	0.804	142	26.1	3060
US Airways Group	0.1470	0.0301	0.0488	3620	1140	0.817	354	60.6	11100
Southwest Airlines Company	0.1020	0.0323	0.0360	3710	1510	0.712	537	73.5	10500
Mesa Air Group	0.1690	0.0103	0.0639	518	155	0.746	159	6.05	1310
Pinnacle Airlines	0.0886	0.0298	0.0067	49.5	14.8	0.734	193	5.42	856
Republic Airways Holdings	0.1030	0.0191	0.0248	328	102	0.734	221	9.7	1460
Ryanair Holdings	0.0699	0.0108	0.0171	1230	470	0.790	163	34.5	3470
SkyWest	0.1520	0.0329	0.0550	1220	367	0.777	442	17.1	3470
United Continental Holdings, Inc.	0.1570	0.0317	0.0568	7720	2180	0.810	409	110	18400
ExpressJet	0.1140	0.0315	0.0181	228	173	0.759	244	9.56	1280
AMR CORP	0.1390	0.0407	0.0551	9010	2690	0.806	626	132	20700

Gallons of fuel used is the total amount of fuel used by an airline's aircraft. Gallons of fuel used is largely dependent on an airline's fleet size and available seat miles but can also be an indication of an airline's fleet age. For example, Northwest's newer Airbus A330 uses 38% less fuel than the DC-10's they replaced. Therefore, investments in new, more fuel-efficient aircraft are often part of a long-term strategy to reduce future gallons of fuel used and thus overall fuel expenses.

Load factor is a metric used primarily in the transportation industry. A company's load factor is defined as a percentage of the available seats filled. Companies can determine the minimum load factor they need to meet in order to break even financially. That is, once a company meets a certain load factor, the revenues from doing so will cover the costs of providing seat capacity. If a company is below this break-even load factor, the company will be spending more than it is earning and will lose money.

Fleet size is the number of airplanes in the airline's fleet. It includes all aircraft a company owns or leases. The larger the fleet size, the more available seat miles or capacity an airline has available to sell to passengers. However, higher maintenance expenses usually accompany larger fleets, so fleet size does not provide a useful comparison between airlines.

Revenue passenger miles is calculated by multiplying the number of paying passengers by the number of miles that they travel. For example, if 100 passengers flew 2,000 miles, it would generate 200,000 revenue passenger miles (RPMs). RPMs are used as a basic measure of airline traffic; when compared to available seat miles, RPMs show how many available seats the airline actually sold relative to its overall capacity.

Passenger revenue includes ticket fares and money spent by passengers on items such as food and bag checks.

Under the standard DEA model, for example, the CCR Equation 1 (Charnes, Cooper, & Rhodes, 1978), load factor, fleet size, revenue passenger miles, and passenger revenue can be treated as outputs; the remaining five factors can be treated as inputs.

$$
\begin{aligned}
&\text{Max} \sum_{r=1}^{s} u_r y_{ro} \\
&\text{s.t.} \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0,\ j = 1,2,....,n, \\
&\sum_{i=1}^{m} v_i x_{io} = 1, \\
&u_r \ge 0, r = 1,2,...,s; v_i \ge 0, i = 1,2,...,m.
\end{aligned}
\tag{1}
$$

where inputs are x_{ij}, (i = 1, 2, …, m) and outputs are y_{rj}, (r =1, 2, …, s).

Based upon the recent development in Liang, Cook, and Zhu (2008), nine factors related to the performance of airlines can be grouped into a two-stage process, as shown in Figure 1.

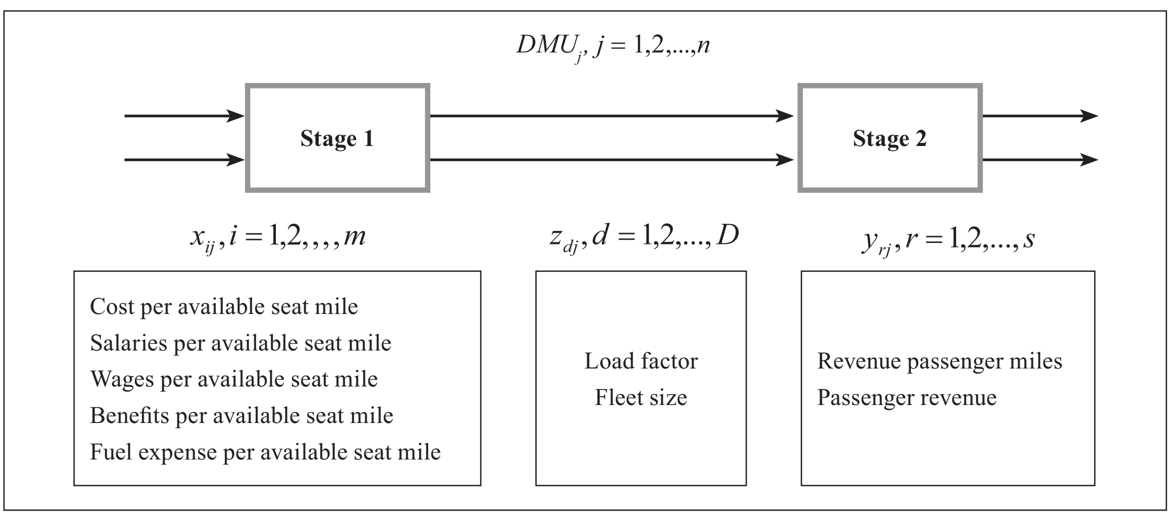

Figure 1. Airline two-stage performance.

In the first stage, cost measures (cost per available seat mile; salaries, wages, and benefits per available seat mile; fuel expense per available seat mile; fuel cost; and gallons of fuel used) are inputs to the outputs of load factor and fleet size. The goal is to minimize the costs and usage of fuel given the load factor and fleet size. In the second stage, load factor and fleet size are used as "resources" to generate revenues for the airlines. In Figure 1, load factor and fleet size are treated as intermediate measures whose optimal values are determined via a centralized model.

To introduce the centralized model in Liang, Cook, and Zhu (2008), the notion for intermediate measures needs to be included, namely, it is assumed DMU_j (j =1, 2, …, n) has D intermediate measures Z_{dj}, (d =1, 2, …, D).

For DMU_j we denote the efficiency for the first stage as e_j^1 and the second as e_j^2. Based upon the DEA model of Charnes, Cooper, and Rhodes (1978), we define

$$e_j^1 = \frac{\sum_{d=1}^{D} w_d z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} \text{ and } e_j^2 = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D} \tilde{w}_d z_{dj}}, \tag{2}$$

where v_i, w_d, $\tilde{w}_d$, and u_r are unknown non-negative weights. It is noted that w_d is set equal to $\tilde{w}_d$ in Liang, Cook, and Zhu (2008). As a result, $e_o^1 \bullet e_o^2$ becomes $\frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$. Therefore, the centralized model can be presented as

$$e_o^{centralized} = \text{Max } e_o^1 \bullet e_o^2 = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{3}$$

s.t.

$$e_j^1 \le 1 \text{ and } e_j^2 \le 1 \text{ and } w_d = \tilde{w}_d .$$

Model (3) can be converted into the following linear program:

$$e_o^{centralized} = \text{Max} \sum_{r=1}^{s} u_r y_{ro}$$

s.t.

$$\begin{aligned}
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} w_d z_{dj} \le 0, \ j = 1,2,....,n, \\
&\sum_{d=1}^{D} w_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \ j = 1,2,....,n, \\
&\sum_{i=1}^{m} v_i x_{io} = 1, \\
&w_d \ge 0, \ d = 1,2,...,D; \ v_i \ge 0, \ i = 1,2,...,m; \ u_r \ge 0, \ r = 1,2,...,s.
\end{aligned} \tag{4}$$

Model (4) gives the overall efficiency of the two-stage process. Assume the above model (4) yields a unique solution. The efficiencies for the first and second stages are obtained, namely

$$e_o^{1,Centralized} = \frac{\sum_{d=1}^{D} w_d^* z_{do}}{\sum_{i=1}^{m} v_i^* x_{io}} = \sum_{d=1}^{D} w_d^* z_{do} \text{ and } e_o^{2,Centralized} = \frac{\sum_{r=1}^{s} u_r^* y_{ro}}{\sum_{d=1}^{D} w_d^* z_{do}}. \quad (5)$$

If we denote the optimal value to model (4) as $e_o^{centralized}$, then we have $e_o^{centralized} = e_o^{1,Centralized} \bullet e_o^{2,Centralized}$. Note that optimal multipliers from model (4) may not be unique, meaning that $e_o^{1,Centralized}$ and $e_o^{2,Centralized}$ may not be unique. Liang, Cook and Zhu (2008) develop models for testing whether an efficiency decomposition is unique.

Application

The standard DEA model (1) is applied first to the airlines in 2007 and 2008 respectively. Note that due to the availability of data, there are 21 and 17 airlines in 2007 and 2008, respectively. Table 3 reports the CCR efficiency scores. It can be seen most of the airlines are efficient; only five are inefficient in each year.

Table 3
Standard DEA Efficiency

Airline	2007	2008
AirTran Holdings	0.85592	0.78943
Allegiant Travel Company	1.00000	1.00000
Alaska Air Group	0.94768	0.74585
Continental Airlines	1.00000	N/A
China Eastern Airlines	1.00000	N/A
Delta Air Lines Inc.	1.00000	1.00000
Frontier Airlines Holdings	1.00000	1.00000
Gol Intelligent Airlines Inc.	0.85857	N/A
Hawaiian Holdings Inc	1.00000	0.85862
JetBlue Airways	1.00000	0.81497
US Airways Group	1.00000	1.00000
Lan Airlines S.A.	0.64006	N/A
Southwest Airlines Company	1.00000	1.00000
Mesa Air Group	1.00000	1.00000
Pinnacle Airlines	N/A	1.00000
Republic Airways Holdings	1.00000	1.00000
Ryanair Holdings	1.00000	1.00000
SkyWest	1.00000	1.00000
United Continental Holdings, Inc.	1.00000	1.00000
ExpressJet	1.00000	0.98471
Northwest Airlines	0.92689	N/A
AMR CORP	1.00000	1.00000

Note. N/A= data are not available.

Tables 4 and 5 report the results from Model 4 and the efficiency decomposition based upon (5). Note that because of the existence of intermediate measures, it is possible that none of the DMUs is efficient. Chen, Cook, and Zhu (2010) developed a procedure for identifying the frontier for a centralized model (4). In both years, AMR Corp, Delta, United/Continental, China Eastern Airlines, Southwest Airlines, Northwest, and US Airways are top ranked based upon the overall centralized scores.

Table 4
Centralized Results in 2007

Airline	Centralized Efficiency $e_o^{centralized}$	Rank	$e_o^{1,Centralized}$	$e_o^{2,Centralized}$
AirTran Holdings	0.19781	13	0.81132	0.24382
Allegiant Travel Company	0.07782	21	0.28404	0.27396
Alaska Air Group	0.24246	11	0.81510	0.29746
Continental Airlines	0.74526	4	0.74526	1.00000
China Eastern Airlines	0.68124	5	1.00000	0.68124
Delta Air Lines Inc.	0.88841	2	0.94667	0.93846
Frontier Airlines Holdings	0.13650	16	0.35419	0.38537
Gol Intelligent Airlines Inc.	0.21504	12	0.49586	0.43366
Hawaiian Holdings Inc	0.10369	20	0.13362	0.77596
JetBlue Airways	0.31445	10	0.88645	0.35473
US Airways Group	0.56099	8	0.80054	0.70076
Lan Airlines S.A.	0.12907	18	0.40227	0.32085
Southwest Airlines Company	0.62276	6	1.00000	0.62276
Mesa Air Group	0.14562	15	1.00000	0.14562
Republic Airways Holdings	0.11732	19	1.00000	0.11732
Ryanair Holdings	0.45587	9	1.00000	0.45587
SkyWest	0.19300	14	1.00000	0.19300
United Continental Holdings, Inc.	0.79741	3	0.79741	1.00000
ExpressJet	0.12936	17	1.00000	0.12936
Northwest Airlines	0.61676	7	0.84214	0.73237
AMR CORP	0.95089	1	0.95089	1.00000

Table 5
Centralized Results in 2008

Airline	Centralized Efficiency $e_o^{centralized}$	Rank	$e_o^{1,Centralized}$	$e_o^{2,Centralized}$
AirTran Holdings	0.23212	8	0.50675	0.45806
Allegiant Travel Company	0.08363	17	0.22142	0.37769
Alaska Air Group	0.19147	10	0.41528	0.46107
Delta Air Lines Inc.	0.69229	2	1.00000	0.69229
Frontier Airlines Holdings	0.22000	9	0.37653	0.58429
Hawaiian Holdings Inc	0.10797	15	0.12223	0.88335
JetBlue Airways	0.30709	7	0.67465	0.45518
US Airways Group	0.46709	6	0.70325	0.66419
Southwest Airlines Company	0.62791	4	1.00000	0.62791
Mesa Air Group	0.18314	11	1.00000	0.18314
Pinnacle Airlines	0.10442	16	1.00000	0.10442
Republic Airways Holdings	0.16320	13	1.00000	0.16320
Ryanair Holdings	0.58088	5	1.00000	0.58088
SkyWest	0.17996	12	1.00000	0.17996
United Continental Holdings, Inc.	0.63948	3	0.63948	1.00000
ExpressJet	0.14039	14	0.96367	0.14568
AMR CORP	0.82750	1	0.84371	0.98078

According to www.wikinvest.com, most commercial airline companies declined after the terrorist events of 9/11 because consumers flew less for business and leisure. In addition to the declining consumer demands, oil prices were rising. Fuel cost is the major expense for commercial airline companies. Some companies such as Southwest had the foresight to lock in low fuel prices using hedging strategies, but most airlines, for example, United Airlines, have no hedging strategies. This is reflected in the centralized model. Southwest is efficient under the first stage for both years. United is highly ranked, but its first stage performance was not ideal, and its high overall efficiency was because of efficient performance in the second stage.

In 2007, 7 out of 23 (33%) airlines achieved 100% efficiency in the first stage of fleet maintenance, but only 3 achieved 100% in the second stage of revenue generation. This result indicates most of the airlines were not efficient using their fleets to generate passenger revenues. That Lan Airlines has the lowest standard DEA efficiency score is noted. Yet, its centralized score is ranked 18. On the other hand, some airlines that are efficient under the standard DEA are ranked very low under centralized scores, for example, Allegiant Travel Company, Hawaiian Holdings, and Republic Airways. This result indicates the standard DEA model does not measure some of the inefficiencies in these airlines' operations. In fact, Allegiant Travel Company's efficiency ratings for the two stages are very low, Hawaiian Holdings is very inefficient in the first stage, and while Republic Airways is efficient under the first stage, its second stage performance is the worst.

In 2008, 7 out of 17 airlines achieved 100% efficiency in the first stage, and only 1 (United) achieved 100% efficiency in the second stage. Those airlines efficient under the first stage in 2007 were also efficient in 2008, indicating the companies performed well with respect to the first stage operation of efficiently maintaining their fleet sizes. Similar to the situation in 2007, airlines were not efficient in using their fleets to generate passenger revenues. Alaska Air Group had the lowest standard DEA score (0.74585), yet its overall centralized efficiency score is ranked 10. Allegiant Travel Company was the worst performer under the centralized model (4), yet it is efficient under the standard DEA model (1). In addition, Express Jet, which has a high efficiency rating under model (1), is ranked 14. This result indicates that simply classifying all performance factors as inputs and outputs in the standard DEA model may not completely identify inefficiency in performance.

Bowen and Headley (2009) provided US airline quality ratings for both 2007 and 2008. Their airline quality rating was a weighted average of multiple elements including on-time performance, denied boarding, mishandled baggage, and customer complaints based upon the U.S. Department of Transportation's monthly *Air Travel Consumer Report*. Interestingly, the airline quality rating had a strong negative correlation with the centralized efficiency scores calculated in this study in both years. For example, Delta was ranked 10 and 12 in 2007 and 2008 by Bowen and Headley, but Delta was a top ranked at 2 based upon the centralized model used in this study. The exception seems to be United whose airline quality rating was ranked 8 and centralized efficiency ranked at 3. This result indicates the US airlines needs to balance their operation efficiency and the quality of their services.

Conclusions

As pointed out in Liang, Cook, and Zhu (2008), in many DEA situations, DMUs may take the form of multiple stages with intermediate measures. It has been recognized that standard DEA models do not appropriately address such multi-stage structures. In this paper, the centralized model developed by Liang, Cook, and Zhu (2008) was used to study the performance of the airline industry in 2007 and 2008. It has been shown that the centralized model has more discriminate power than does the standard DEA model. While the standard DEA model deems most of the airlines efficient, the centralized model is able to evaluate an airline's performance with respect to its fleet operation efficiency and performance on passenger revenue generation.

In the current analysis, freight revenue was not included as an output from the second stage. This is because freight revenue data for about 50% of the airlines was not available. With the centralized models, the efficiencies of fleet maintenance and revenue generation are evaluated simultaneously to determine a set of optimal weights on the intermediate measures (fleet size and load factor) that maximizes the aggregate efficiency score in a joint decision-making process. If the leader-follower model of Liang, Cook, and Zhu (2008) were to be adopted, Stage 1 (fleet maintenance) is the leader whose performance is more important and could be assumed and optimized first. The performance of Stage 2 (revenue generation), as the follower, would be computed subject to the requirement that the leader's efficiency remains fixed. Similarly, Stage 2 can be assumed to be the leader and optimized first, while Stage 1 is assumed to be the follower. Because information about whether the airlines use the simultaneous or leader-follower strategy for their operations is unknown, it is believed that the centralized approach (for the simultaneous strategy) would lead to the more "neutral" measurement of their performances; it is also believed airlines have total control over the two stages of operation. The analysis can be modified with the leader-follower approach if exact information about an airline's operation strategy were to be available.

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The author is grateful for the comments and suggestions made by an anonymous reviewer.