BENCHMARKING THE OPERATING EFFICIENCY OF U.S. AIRLINES USING DEA

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ABSTRACT

The financial meltdown that made headlines in September and October 2008 left many banks, insurance companies, automakers, and other institutions struggling for survival, and exacerbated the economic slowdown that was already underway in the US and abroad. The ensuing recession had a very negative impact on the airline industry in the United States with losses that ran into billions. In this paper, we illustrate the use of data envelopment analysis, an operations research technique, to analyze the operating efficiency of the U.S. airline industry by benchmarking a set of ratios that assess the operating efficiency of a firm against its peers. Data envelopment analysis clearly brings out the airline(s) that is (are) operating more efficiently in comparison to other airlines in the industry, and points out the areas in which poorly performing airlines need to improve.

Keywords: Benchmarking, Data Envelopment Analysis, Airline, Operational Efficiency.

INTRODUCTION

The financial meltdown that made headlines in September and October 2008 left many banks, insurance companies, automakers, and other institutions struggling for survival, and exacerbated the economic slowdown that was already underway in the US and abroad. The resulting stock market and housing market struggles left many consumers feeling poorer and less inclined (or able) to open their wallets. As a result, both consumer and business spending dampened considerably. In addition, the tightness of financial markets has limited airlines' access to capital markets. According to Standard & Poor's calculations, the 10 largest US airlines lost about $4.7 billion in 2009, as a sharp drop in demand, particularly among business travelers, more than offset the sharp drop in oil prices that led to much lower jet fuel costs. The drop-off in business and leisure travel demand led to significant yield degradation and a much less profitable passenger mix, as many more leisure travelers flying on discounted tickets took the place of business travelers. The industry was profitable in 2006 and 2007 following five years of multibillion-dollar losses, but was unprofitable in 2008 on rising fuel costs throughout the year. Although the airline industry's operating environment has been brutal since 2001, carriers that operated with low costs and low fares were generally able to cope better than their higher-cost counterparts were.

The airline industry is both labor- and capital-intensive. Additionally, fuel costs have absorbed a growing portion of revenues in recent periods. As of December 31, 2009, the US commercial aviation industry consisted of 18 major air carriers (those flying aircraft with over 90 seats) and 66 regional carriers (using smaller piston, turboprop, and jet aircraft), according to the Federal Aviation Administration (FAA). The FAA also estimates that the number of aircraft in the US commercial fleet, including regional carriers, totaled 7,123 at the end of 2009, a decrease of 323 aircraft from the end of 2008. The 2009 number included 3,666 mainline air carrier passenger aircraft (jets with more than 90 seats), 845 all-cargo aircraft, and 2,612 regional aircraft (smaller jets, turboprops, and pistons).

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In this paper, we analyze the operating efficiency of the eight largest U.S. commercial airlines. Several recent trends and events have provided increased scrutiny of the industry, and of its financial performance.The recent history of the airline industry has been one of shrinkage, fueled by consolidation and bankruptcies. Mergers, capacity cuts, bankruptcy filings, large-scale losses, and high debt levels are the legacy of the first decade of the new millennium, and represent challenges that are likely to persist for some time. In 2010, United Airlines merged with Continental Airlines. Northwest Airlines had merged with Delta Airlines. Southwest Airlines has recently announced plans to acquire Air Tran.Airlines are currently fighting the perception that they are a major source of greenhouse gases by listing all the ways they have reduced jet fuel usage over the past 10 years: modernizing their fleets to more fuel efficient planes, efforts to control fuel use, and modifications to existing planes to increase fuel efficiency, to name a few. Though the airlines may have undertaken these initiatives to cut costs in the wake of high oil prices, they are using their accomplishments as a way to ease environmental concerns. Global recession is hurting this industry more than anything else due to decline in business and leisure travel and as a result, chapter 11 bankruptcies loom for smaller regional air carriers. Since the terrorist strikes in 2001, a number of federally mandated security measures have been put into effect—both to reassure the flying public and to prevent future occurrences. Airlines are now required to either screen all bags for explosives or make sure each bag is matched to a passenger seated on that flight—time-consuming and expensive initiatives.High crude oil prices continue to remain a concern for the airline industry and a source of concern and losses.

PREVIOUS STUDIES

Numerous studies have analyzed the operating efficiency of firms using data envelopment analysis models. Hung, Lu, and Wang (2010) explore the operating efficiency, the scale efficiency targets, and the variability of DEA efficiency estimates of Asian container ports. Joo, Min, Kwon, and Kwon (2010) use data envelopment analysis to assess the operating efficiency of specialty coffee retailers from the perspective of socially responsible global sourcing. They evaluate the impact of socially responsible sourcing on the operating efficiencies of specialty coffee retailers before and after implementing fair-trade practices. Their study also compares the operating efficiencies of fair-trade coffee retailers to those of non-fair-trade coffee retailers. Hung and Lu (2008) study applies the Data Envelopment Analysis (DEA) approach with the classical radial measure, non-radial efficiency measure and efficiency achievement measure, respectively, combining multiple outputs and inputs to measure the magnitude of performance differences between the IC firms. Shimshak and Lenard (2007) present a Two-Model approach for including quality measures in DEA studies. This approach allows decision-makers to evaluate two models simultaneously, one measuring operational efficiency and the second measuring quality efficiency. This new method selects only DMUs that are efficient in both operational and quality measures to be members of the benchmark set. Their study demonstrates the Two-Model DEA approach using data from the nursing home industry. Lu, Yang, Hsiao, and Lin (2007) study uses the CCR model of Data Envelopment Analysis (DEA) and the slack variable analysis to evaluate the operating efficiency of the domestic banks in Taiwan from 1998 to 2004. Using data from the Annual Survey of Hospitals compiled by the Department of Health in Taiwan for years 1994 through 1997, Chang, Chang, Das, and Li (2004) use Data Envelopment Analysis (DEA) to evaluate the impact of a National Health Insurance (NHI) Program on the operating efficiency of district hospitals in Taiwan. Anderson, Fok, Springer, and Webb (2002) measure the technical efficiency and economies of scale for real estate investment trusts (REIT) by employing data envelopment analysis (DEA). Using data from the National Association of Real Estate Investment Trusts (NAREITs) for the years 1992-1996, they report that REITs are technically inefficient, and the inefficiencies are a result of both poor input utilization and failure to operate at constant returns to scale. Golany, Roll, and Ryback (1994) study applies data envelopment analysis (DEA) for measuring and evaluating the operating efficiency of power plants in the Israeli Electric Corporation is discussed.

In this paper, we extend previous studies by illustrating the use of DEA models to benchmark the performance of airline industry in terms of financial performance. No previous study has airlines in terms of financial performance.

MODEL

The Data Envelopment Analysis Model

The Data Envelopment Analysis (DEA) (Charnes et al., 1978) is a widely used optimization-based technique that measures the relative performance of decision making units that are characterized by a multiple objectives and/or multiple inputs structure. Data envelopment analysis is a technique used to assess the comparative efficiency of homogenous operating units such as schools, hospitals, utility companies, sales outlets, prisons, and military operations. More recently, it has been applied to banks (Haslem, Scheraga, & Bedingfield, 1999) and mutual funds (Haslem & Scheraga, 2003; Galagedera & Silvapulle, 2002; McMullen & Strong, 1998; Murthi, Choi, & Desai, 1997). It is a powerful technique for measuring performance because of its objectivity and ability to handle multiple inputs and outputs that can be measured in different units. The DEA approach does not require specification of any functional relationship between inputs and outputs, or a priori specification of weights of inputs and outputs. DEA provides gross efficiency scores based on the effect of controllable and uncontrollable factors.

The DEA methodology measures the performance efficiency of organization units called Decision-Making Units (DMUs). This technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs. The performance of DMUs is assessed in DEA using the concept of efficiency or productivity defined as a ratio of total outputs to total inputs. Efficiencies estimated using DEA are relative, that is, relative to the best performing DMU or DMUs (if multiple DMUs are the most efficient). The most efficient DMU is assigned an efficiency score of unity or 100 percent, and the performance of other DMUs vary between 0 and 100 percent relative to the best performance.

Consider a set of n observations on the DMUs. Let us define the following:

$j = 1,2,\ldots\ldots,n$ DMU.

$i = 1,2,\ldots\ldots,m$ inputs

$r = 1,2,\ldots\ldots,s$ outputs

Each observation, DMU_j, $j = 1,2,\ldots..,n$, uses:

x_{ij} – amount of input i for unit j, $i = 1,2,\ldots\ldots,m$ and $j = 1,2,\ldots.,n$.

y_{rj} – amount of output r for unit j, $r = 1,2,\ldots..,s$ and $j = 1,2,\ldots.,n$.

u_r – weight assigned to output r, $r = 1,2,\ldots..,s$

v_i – weight assigned to input i, $i = 1,2,\ldots\ldots,m$.

The DEA methodology gives a measure of efficiency that is defined as the ratio of weighted outputs to weighted inputs. The most important issue in this method is the assessment of the weights. Charnes et. al. define the efficiency measure by assigning to each unit the most favorable weights. In general, the weights will not be the same for different units. Further, if a unit happens to be inefficient, relative to the others, when most favorable weights are chosen, then it is inefficient, independent of the choice of weights. Given these weights, the efficiency of a DMU in converting the inputs to outputs can be defined as the ratio of weighted sum of output to weighted sum of inputs.

$$\text{Efficiency} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \qquad (1)$$

The weights for a DMU are determined using mathematical programming as those that will maximize the efficiency of a DMU subject to the condition that the efficiency of other DMUs (calculated using the same set of weights) is restricted to values between 0 and 1. The weights are chosen that only most efficient units will reach the upper bound of the efficiency measure, chosen as 1. Let us take one of the DMUs, say the oth DMU as the reference DMU under evaluation whose efficiency (E_o) is to be maximized. Therefore, to compute the DEA efficiency measure for the oth DMU, we have to solve the following fractional linear programming model:

$$\max E_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad (2)$$

Subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \; j = 1,..,n \qquad (3)$$

$u_r \ge \varepsilon$, r = 1,…,s
$v_i \ge \varepsilon$, i = 1,….,m

Where ε is an infinitesimal or non-Archimedean constant that prevents the weights from vanishing (Charnes, et. al., 1994). When we solve the above mathematical program, we get the optimal objective function (2) that represents the efficiency of DMU_o. If the efficiency is unity, then the firm is said to be efficient, and will lie on the efficiency frontier. Otherwise, the firm is said to be relatively inefficient. To find the efficiency measure of other DMUs, we have to solve the above mathematical program by considering each of the DMUs as the reference DMU. Therefore, we obtain a Pareto efficiency measure where the efficient units lie on the efficiency frontier (Thanassoulis, 2001). The fractional mathematical programs are generally difficult to solve. To simplify them, we should convert them to a linear program format. The fractional program (2), (3) can be conveniently converted into an equivalent linear program by normalizing the denominator using the constraint $\sum_{i=1}^{m} v_i x_{io} = 1$. As the weighted sum of inputs is constrained to be unity and the objective function is the weighted sum of outputs that has to be maximized.

$$\max \sum_{r=1}^{s} u_r y_{ro} \qquad (4)$$

Subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1, \qquad (5a)$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \; j = 1,..,n, \qquad (5b)$$

$u_r \ge \varepsilon$, r = 1,…,s
$v_i \ge \varepsilon$, i = 1,….,m

This model is the CCR (Charnes, Cooper, and Rhodes) model. Similarly, a general input minimization CCR model can be represented as

$$\min \sum_{i=1}^{m} v'_i x_{io} \qquad (6)$$

Subject to

$$\sum_{r=1}^{s} u'_r y_{ro} = 1 \qquad (7a)$$

$$\sum_{r=1}^{s} u'_r y_{rj} - \sum_{i=1}^{m} v'_i x_{ij} \le 0, \; j = 1,..,n, \qquad (7b)$$

$u_r \ge \varepsilon$, r = 1,…,s
$v_i \ge \varepsilon$, i = 1,….,m

According to the basic linear programming, every linear programming problem (usually called the primal problem) has another closely related linear program, called its dual. Therefore, the dual of the output maximizing DEA program is as follows:

$$\theta^* = \min \theta \qquad (8)$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}, \; i = 1,….,m \qquad (9a)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, \; r = 1,…,s \qquad (9b)$$

$\lambda_j \ge 0$,
θ unrestricted.

If $\theta^* = 1$, then the current input levels cannot be reduced, indicating that DMU_o is on the frontier. Otherwise, if $\theta^* < 1$, then DMU_o is dominated by the frontier. θ^* represents the input-oriented efficiency score of DMU_o. The individual input reduction is called slack. In fact, both input and output slack values may exist in model (8)

$$s_i^- = \theta^* x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \quad i = 1,….,m$$

$$s_r^+ = \sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro}, \quad r = 1,…,s \qquad (3.10)$$

To determine the possible non-zero slacks after solving the linear program (8), we should solve the following linear program:

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta^* x_{io}, \; i = 1,….,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \; r = 1,…,s \qquad (11)$$

$\lambda_j \ge 0$,
θ unrestricted.

DMU_o is efficient if and only if $\theta^* = 1$ and $s_i^{-*} = s_r^{+*} = 0$ for all i and r. DMU_o is weakly efficient if and only if $\theta^* = 1$ and $s_i^{-*} \ne 0$ and (or) $s_r^{+*} \ne 0$ for some i and r. In fact models (8) and (9) represent a two-stage DEA process that can be summarized in the following DEA model:

$$\min \quad \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}, \; i = 1,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \; r = 1,\ldots,s \qquad (12)$$

$$\lambda_j \geq 0,$$

$$\theta \text{ unrestricted.}$$

DATA AND METHODOLOGY

We used the data available from Standard & Poor's Netadvantage for this study. We used three operational efficiency variables (year 2009) to evaluate eight United States airlines. Eight companies that we include in our study are: Airtran, Alaska, AMR, Delta, JetBlue, Southwest, USAir, and United Airlines. These are the eight largest airlines operating in United States. We benchmark the operational performance of these companies on the basis of the following functional variables: Operating Cost as Percentage of Revenue– Operating Cost as Percentage of Revenue is the sum of fuel expense as percentage of revenue and labor cost as percentage of revenue, Fixed Assets Turnover Ratio - Fixed Assets Turnover Ratio is the ratio of Sales and Net property and plant equipment, Passenger Load Factor - Passenger Load Factor is an indicator of the capacity utilization of the airline. Table 2 illustrates the pooled data of the eight airlines used for analysis.

Data Envelopment Model Specifications for the Airline Industry

Besides the mathematical and computational requirements of the DEA model, there are many other factors that affect the specifications of the DEA model. These factors relate to the choice of the DMUs for a given DEA application, selection of inputs and outputs, choice of a particular DEA model (e.g. CRS, VRS, etc.) for a given application, and choice of an appropriate sensitivity analysis procedure (Ramanathan, 2003). Due to DEA's non parametric nature, there is no clear specification search strategy. However, the results of the analysis depend on the inputs/outputs included in the DEA model. There are two main factors that influence the selection of DMUs – homogeneity and the number of DMUs. To successfully apply the DEA methodology, we should consider homogenous units that perform similar tasks, and accomplish similar objectives. In our study, the companies are homogenous as they are identified by Standard and Poor's Netadvantage to be competitors. Furthermore, the number of DMUs is also an important consideration. In addition, the number of DMUs should be reasonable so as to capture high performance units, and sharply identify the relation between inputs and outputs. The selection of input and output variables is the most important aspect of performance analysis using DEA. In general, the inputs should reflect the level of resources used or a factor that should be minimized. The outputs reflect the level of the economic variable factor, and the degree to which an economic variable contributes to the overall strength (efficiency) of a company. There are some simple rules of thumb that guide the selection of inputs and outputs, and the number of participating DMUs[1].

To study the performance of the airline industry, we consider three factors to develop the DEA model: operating cost as percentage of revenue, fixed assets turnover ratio, and passenger load factor.

Out of these three factors, we specify operating cost as percentage of revenue and fixed assets turnover ratio as input, because for a given airline the lower these variables are the better the performance of the airline is. Similarly, passenger load factor implies a better-performing company. Thus, we consider this variables as output variables. Finally, the choice of the DEA model is also an important consideration. We should select the appropriate DEA model with options such as input maximizing or output minimizing, multiplier or envelopment, and constant or variable returns to scale. DEA applications that involve inflexible inputs or not fully under control inputs should use output-based formulations. On the contrary, an application with outputs that are an outcome of managerial goals, input-based DEA formulations are more appropriate. In addition, for an application that emphasizes inputs and outputs, we should use multiplier version. Similarly, for an application that considers relations among DMUs, envelopment models are more suitable. Furthermore, the characteristics of the application dictate the use of constant or variable returns to scale. If the performance of DMUs depends heavily on the scale of operation, constant returns to scale (CRS) is more applicable, otherwise variable returns to scale is a more appropriate assumption.

In our study, the comparative evaluation among the airlines is an important consideration. Therefore, we select the envelopment models for our analysis. In addition, the outputs are an outcome of managerial goals. Therefore, input-based formulation is recommended for our study. The objective of the analysis is to suggest a benchmark for the airline firms. Furthermore, to investigate the affect of scale of operations, if any, among the 8 companies, we consider both variable returns to scale and constant returns to scale DEA models. Also, the structure of the DEA model (in envelopment form) uses an equation and separate calculation for every input and output. Therefore, all the input and output variables can be used simultaneously and measured in their own units. In this study, we use the Input-Oriented Variables

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[1] The following are the guidelines for DMU model selection:

a. The number of DMUs is expected to be larger than the product of number of inputs and outputs (Darrat et. Al., 2002; Avkiran, 2001) to discriminate effectively between efficient and inefficient DMUs. The sample size should be at least 2 or 3 times larger than the sum of the number of inputs and outputs (Ramanathan, 2003).

b. The criteria for selection of inputs and outputs are also quite subjective. A DEA study should start with an exhaustive, mutual list of inputs and outputs that are considered relevant for the study. Screening inputs and outputs can be quite quantitative (e.g. statistical) or qualitative that are simply judgmental, use expert advice, or use methods such as analytical hierarchy process (Saaty, 1980). Typically inputs are the resources utilized by the DMUs or condition affecting the performance of DMUs. On the other hand, outputs are the benefits generated as a result of the operation of the DMUs, and records higher performance in terms of efficiency. Typically, we should restrict the total number of inputs and outputs to a reasonable level. As the number of inputs and outputs to a reasonable level. As the number of inputs and outputs increases, more number of DMUs get an efficiency rate of 1, as they become too specialized to be evaluated with respect to other units (Ramanathan, 2003).

Return to Scale (VRS) to evaluate the efficiency of eight companies for the year 2009.

Figure 1 illustrates a decision support system using data envelopment analysis. The decision support system uses the DEA methodology to determine how good a firm is. The DEA-based decision support system uses the company attributes – operating cost as percentage of revenue as input variable. The system uses passenger load factor and fixed assets turnover ratio as output variables to calculate efficiency score for a firm. This score is a relative value computed by comparing the given firm to a pool of well-performing companies that serve as a benchmark for the company under evaluation. Each firm is evaluated against the existing firms with an identical set of inputs or outputs that is constructed as a combination of performing and non performing companies.

By using the existing good companies as a "role model," DEA not only helps differentiate well performing (efficient companies from poorly performing (inefficient) firms, but also brings out the reasons why a company may be underperforming. This helps investors and creditors justify their decisions to invest or not to invest their funds in a particular company. This will also help management identify areas of weakness for a firm so that management plans can focus on plugging the weaknesses or taking steps to counter the weaknesses.

EMPIRICAL ANALYSIS

Each of the airline company is a homogenous unit, and we can apply the DEA methodology to assess the comparative performance of these companies. This study evaluates the status of the airline industry by benchmarking the relative performance of eighteight companies against each other in the industry. Using the DEA methodology, we can calculate an efficiency score for the 8 companies on a scale of 1 to 100. We analyze and compute the efficiency of these companies using the financial statements for the year 2009. Table 3 illustrates the efficiency scores for eight companies. Further, we also study the peers (model companies) for inefficient companies.

Table 3 shows the relative performance of the airline companies benchmarked against each other. Table 3 also shows that one out of eight companies was ranked as efficient till December 2009, and seven companies were inefficient companies. US Air was 100% efficient. On the other hand Airtran, Alaska, AMR, Delta, JetBlue, Southwest, and United Airlines are inefficient. Figure 2 shows the efficiency frontier graph of the pooled company data. The 100% efficient companies (blue dots) are on the efficiency frontier, where as the inefficient companies (red dots) are inside the efficiency frontier. The DEA Analyzer calculates the level of inefficiency by measuring the distance between the efficiency frontier and the inefficient companies. Therefore, an operational manager can use this efficiency frontier to assess the relative efficiency of the firm in the industry. The DEA model compares the operating cost as percentage of revenue, fixed assets turnover ratio, and passenger load factor.

We present the score in percentage value varying between 0% and 100%. We find that the input efficiency of US Air is 100%. On the other hand, the input efficiency of the remaining companies are: Airtran (77%), Alaska (80%), AMR (62%), Delta (76%), JetBlue (7%), Southwest (64%), and United Airlines (88%). This means that the observed level of fixed assets turnover ratio, and passenger load factor for Airtran can be achieved with 77% of the current levels of operating cost as percentage of revenue. The same rationale applies to Alaska (80%), AMR (62%), Delta (76%), JetBlue (7%), Southwest (64%), and United Airlines (88%). Table 4 illustrates the efficiency scores and the corresponding ranking of the pooled companies in the year 2009. The average score is 80%, with four companies having efficiency levels above average while the remaining four are below the average level. The 100% efficient company is,is the best practice company within the pooled database of the Decision Support System. The best practices company US Air is 100% efficient. As all other airlines are inefficient; the next step is to identify the efficient peer group or companies whose operating practices can serve as a benchmark to improve the performance of these companies. Table 5 illustrates the peer group for the inefficient companies. As shown in the Table 5, US Air serves as a peer for Alaska, AMR, Delta, JetBlue, Southwest, and United Airlines as US Air is the only 100% efficient company. Thus, , Alaska, AMR, Delta, JetBlue, Southwest, and United Airlines should emulate US Air.

After calculating the efficiency of a company using DEA, and identifying the efficient peers, the next step in DEA analysis is feasible expansion of the output or contraction of the input levels of the company within the possible set of input-output levels. The DEA efficiency measure tells us whether or not a given company can improve its performance relative to the set of companies to which it is being compared. Therefore, after minimizing the input efficiency, the next stage involves calculating the optimal set of slack values with an assurance that input efficiency will not decrease at the expense of slack values of the input and output factors. Once efficiency has been minimized, the model does seek the maximum sum of the input and output slacks. If any of these values is positive at the optimal solution to the DEA model that implies that the corresponding output of the company (DMU) can improve further after its output levels have been raised by the efficiency factor, without the need for additional input. If the efficiency is 100% and the slack variables are zero, then the output levels of a company cannot be expanded jointly or individually without raising its input level. Further, its input level cannot be lowered given its output levels. Thus, the companies are pareto-efficient with technical output efficiency of 1. If the company is 100% efficient but one slack value is positive at the optimal solution then the DEA model has identified a point on the efficiency frontier that offers the same level on one of the outputs as company A in question, but it offers in excess of the company A on the output corresponding to the positive slack. Thus, company A is not Pareto-efficient, but with radial efficiency of 1 as its output cannot be expanded jointly. Finally, if the company A is not efficient (<100%) or the efficiency factor is less than 1, then the company in question is not Pareto-efficient and efficiency factor is the maximum factor by which both its

observed input levels can be reduced without the changing its output. If at the optimal solution, we have not only input efficiency < 1, but also some positive slack, then the output of company A corresponding to the positive slack can be raised by more than the factor output efficiency, without the need for additional input. The potential additional output at company A is not reflected in its efficiency measure because the additional output does not apply across all output dimensions. Table 6 illustrates the slack values identified in the next stage of the DEA analysis. The slack variables for 100% efficient companies are zero. Therefore, US Air is Pareto-efficient as the DEA model has been unable to identify some feasible production point which can improve on some other input or output level. On the other hand, for Airtran, there is further scope for increasing Sales/Net Property, Plant & Equipment by 1.06 unitsAirtran can follow US Air as its role model and emulate their policies. Similarly, Alaska Airline can increase Sales/Net Property, Plant & Equipment by 1.06 units. . Table 6 illustrates the slack values of the relevant factors for inefficient companies.

SUMMARY AND CONCLUSIONS

Traditional operational efficiency analysis techniques uses fuel cost as a percentage of revenue, labor cost as a percentage of revenue, Sales/Net Property, Plant & Equipment, and percentage load factor to compare a firm's performance against its peers in the industry as well as against the company's historical performance. On the basis of this comparison, analyst will recommend whether the company is doing well or underperforming relative to its peers or relative to its own past performance. DEA employs relative efficiency, a concept enabling comparison of companies with a pool of known efficient companies. The DEA model compares a firm with the pool of efficient companies by creating an efficiency frontier of good firms—a tolerance boundary created by establishing the efficiency of firms in terms of several sets of financial ratios. Companies lying beyond this boundary can improve one of the input values without worsening the others. We found that US Air is 100% efficient. On the other hand Airtran, Alaska, AMR, Delta, JetBlue, Southwest, and United Airlines are inefficient. We also illustrate the areas in which inefficient companies are lacking behind efficient firms.

We also provide an insight into the benefits of DEA methodology in analyzing operational efficiency of the airlines industry. The decision support system stores the company's historical data, competitive firm's data, and other industry specific data, and uses the DEA methodology to analyze a firm's performance. Moreover, DEA modeling does not require prescription of the functional forms between inputs and outputs. DEA uses techniques such as mathematical programming that can handle a large number of variables and constraints. As DEA does not impose a limit on the number of input and output variables to be used in calculating the desired evaluation measures, it's easier for loan officers to deal with complex problems and other considerations they are likely to confront.

APPENDICES

Table 1: Generalized DEA Models

Frontier Type Input-Oriented Output-Oriented

$$\text{Min } \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \qquad \text{Max } \phi - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad i=1,2,\ldots,m \qquad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i=1,2,\ldots,m$$

CRS

$$\sum_{j=1}^{n} \lambda_j x_{rj} + s_r^+ = y_{ro} \quad r=1, 2,\ldots,s; \qquad \sum_{j=1}^{n} \lambda_j y_{rj} + s_r^+ = \phi y_{ro} \quad r=1,2,\ldots,s;$$

$$\lambda_j \geq 0 \quad j=1,2,\ldots n \qquad \lambda_j \geq 0 \quad j=1,2,\ldots n;$$

VRS: Add $\sum_{j=1}^{n} \lambda_j = 1$; NIRS: Add $\sum_{j=1}^{n} \lambda_j \leq 1$; NDRS: Add $\sum_{j=1}^{n} \lambda_j \geq 1$

Where s are the slack variables; x represents input variables; y represent output variables; λ is a scalar factor, and θ and ϕ represent efficiency score of a DMU.

Table 2: Pooled Data Set of Airline Companies for Year 2008

Airline	Operating Cost	Sales/Net Property, Plant & Equip	passenger load factor
Airtran	4.984967	1.774	0.798
Alaska	4.84205	1.073	0.786
AMR	6.205754	1.287	0.8
Delta	5.067883	1.373	0.82
Jet Blue	5.237371	0.708	0.797
Southwest	6.050892	0.973	0.76
USAir	3.851597	2.83	0.819
UAL	4.394245	1.66	0.819

Table 3: DEA Efficiency Scores for the Airline Companies.

A company with 100% score is considered the most efficient and a company with less than 100% score is considered inefficient. Efficiency scores is based on fuel cost as a percentage of revenue, labor cost as a percentage of revenue, sales/net plant and machinery, and passenger load factor.

Company	Efficiency
Airtran	77%
Alaska	80%
AMR	62%
Delta	76%
Jet Blue	97%
Southwest	64%
USAir	100%
UAL	88%

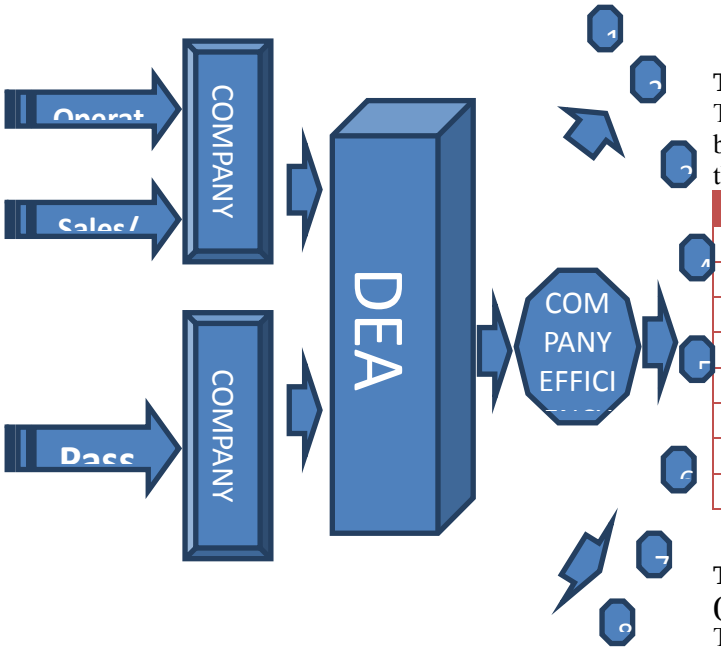

Figure 1: Decision Support System using Data Envelopment Analysis

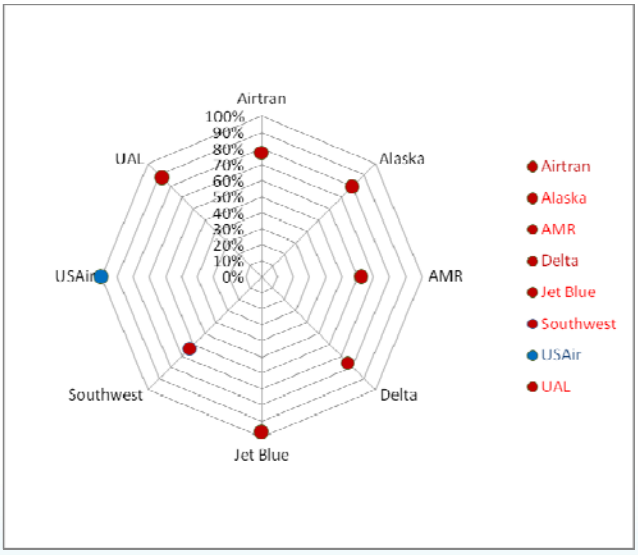

Figure 2: Efficiency Frontier for the Benchmarked Companies.

Table 4: Efficiency Score and Ranking of the 8 Airlines for 2009.

Airline	Efficiency	Rank
USAir	100%	1
Jet Blue	97%	2
UAL	88%	3
Alaska	80%	4
Airtran	77%	5
Delta	76%	6
Southwes t	64%	7
AMR	62%	8
Average	80%	

Table 5: Peer Companies and their weights in percentage

This table shows those companies that can serve as a benchmark for companies with DEA efficiency score of less than 100.

Airline	efficiency	USAir
Airtran	77%	1.00
Alaska	80%	1.00
AMR	62%	1.00
Delta	76%	1.00
Jet Blue	97%	1.00
Southwest	64%	1.00
USAir	100%	1.00
UAL	88%	1.00

Table 6: Slack Variables for Inefficient Companies (efficiency < 100%) (2008)

Table shows the adjustment needed in each of the three operational variables for an inefficient company to become efficient.

Airline	*efficiency*	*Operating Cost*	*Sales/Net Property, Plant & Equip*
Airtran	77%	0.00	1.06
Alaska	80%	0.00	1.06
AMR	62%	0.00	1.76
Delta	76%	0.00	1.54
Jet Blue	97%	1.22	0.00
Southwes t	64%	1.22	0.00
USAir	100%	0.00	0.00
UAL	88%	0.00	1.17

REFERENCES

Available upon request from the author.