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How efficient airways act as role models and in what dimensions? A superefficiency DEA model enhanced by social network analysis

Umut Aydın [a], Melis Almula Karadayi [b], Füsun Ülengin [c,*]

[a] Bandırma Onyedi Eylül University, Faculty of Engineering and Natural Sciences, Department of Transportation Engineering, Bandırma, Balıkesir, 10200, Turkey
[b] Istanbul Medipol University, Faculty of Engineering and Natural Sciences, Department of Industrial Engineering, Beykoz, Istanbul, 34810, Turkey
[c] Sabanci University, School of Management, Tuzla, Istanbul, 34945, Turkey

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ABSTRACT

In this empirical study, a five-stage methodology is used to examine the efficiency of 45 worldwide known airline companies from the financial, operation and marketing perspectives. Initially, the superefficient data envelopment model is run with inputs and outputs that are selected based on the literature review. However, because 21 out of 45 airline companies are found to be efficient based on this analysis, a stepwise regression-based mechanism is applied to four reduced models – one for each output variable – for better discrimination. The outputs are, namely, net profit margin (financial output), passengers carried, on-time departure performance (operational outputs), and customer satisfaction (marketing output). In this way, the significant input variables are found for each reduced model. In the third stage, in order to provide even more discrimination, social network-based eigenvector centrality values are used as the weights of the superefficiency scores, and the strengths and weaknesses of efficient airlines for each output are specified in terms of their related significant inputs. The results show that, when net profit margin is taken as an output, Vietnam Airlines has the top weighted superefficiency value and excels in terms of available seat kilometers and liquidity, but it should improve its debt level. Although Norwegian Airlines has the highest efficiency with respect to debt level, it is not the best role model because its eigenvector centrality value is relatively low. However, Norwegian airlines also has the highest weighted superefficiency and acts as a role model in terms of on-time departures with respect to this output. Its main strength is liquidity, and it has no significant weaknesses. On the other hand, in terms of overall satisfaction and passengers carried, Vietnam Airlines and Thai Airways are the leaders, respectively. Vietnam Airlines is the only superefficient company with respect to overall satisfaction, while the basic strengths of Thai Airways in terms of passengers carried are its employee and fleet, and it has no significant weakness. A final aggregation of the results is made by making pairwise comparisons of the relative importance of four outputs for 7 experts selected from different departments of airline companies. According to the results, Net Profit Margin has the highest priority, followed by On-time Departure and Overall Customer Satisfaction, while passengers carried has the lowest importance. Based on these relative priorities, it can be said that Vietnam Airlines can be accepted as the top performing airline company, followed by Norwegian Airlines.

1. Introduction

Today, airline companies are facing important financial, operational and customer service performance fluctuations. To improve the competitiveness of airline companies, it is necessary to use appropriate tools to measure their efficiencies in these dimensions. However, the efficiency evaluation is difficult because of the large number of complex factors involved. For example, a focus on service quality may help to increase customer satisfaction and, hence, improve service productivity, but the operational and financial performance may be subsequently reduced as a result. Contrarily, decisions to improve an airline's operational and financial performance regardless of customer satisfaction may result in internal and external factors that can cause a number of negative reactions. As seen, the problem has a multidimensional aspect. On the other hand, the results are also heavily influenced by the variables that are taken into account (Colli et al., 2011).

This study proposes an integrated superefficiency Data Envelopment Analysis (DEA) model with a stepwise regression-based feedback

* Corresponding author.
E-mail addresses: uaydin@bandirma.edu.tr (U. Aydın), makaradayi@medipol.edu.tr (M.A. Karadayi), fulengin@sabanciuniv.edu (F. Ülengin).

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mechanism and social network analysis to evaluate the performance of the world's 45 major airline companies. The superefficiency DEA results are weighted with eigenvector centrality values to discriminate among the efficient airline companies. Based on the network-based analysis proposed by Liu and Lu (2010), the strengths and weaknesses of each efficient airline company are analyzed in detail for each considered output. For this purpose, a directed and weighted graph is constructed, in which the nodes represent the airline companies and the edges represent their relationships. This method can rank efficient DMUs, taking into account their qualities by utilizing the eigenvector centrality concept. This analysis aims develop a road map to specify the basic improvement areas in which each airline company should focus and make investments. The basic contributions of the study can be summarized as follows:

1. The inputs and outputs are initially specified based on a literature survey. The lack of nonfinancial measures encountered in the literature is addressed by taking into account the customer satisfaction surveys and the operational indicators.
2. For each output, the most significant inputs are selected by using stepwise backward variable regression analysis. In this way, the less significant variables are eliminated from consideration.
3. Although the stepwise regression-based backward variable selection technique is used with the classic DEA method (see section 2.2), its use with the superefficiency DEA model is a novel approach in the literature and increases the discriminatory and ranking power of the traditional DEA model.
4. Subsequently, Social Network Analysis is used to specify each output variable for which efficient airline companies are leaders and role models in terms of input variables selected by stepwise regression analysis. The use of eigenvector centrality as a weight is itself a new concept in the group decision-making literature. Its application to find the weighted average of the superefficiency scores provides greater discriminatory power in the ranking of the efficient airline companies and a novel contribution to the airline management literature. Therefore, a benchmark is obtained for the airline companies to improve their effectiveness in different dimensions by analyzing the strengths and weaknesses of the role model in each dimension.
5. A final selection of the most efficient airline companies is made based on the aggregation of the efficiency results for the financial, operations and marketing efficiencies. A pairwise comparison survey is conducted with 7 experts on airline companies who are selected from different departments to represent different perspectives. The relative weights of these outputs are specified using the eigenvalues corresponding to the largest eigenvector, and the experts' opinions are aggregated using geometric means.

The next section provides the literature survey on airline efficiency measurement and the variable selection methods. The third section provides the proposed methodology and its application to the worldwide known 45 airline companies, which also underlines the managerial implications for each output based on the superefficiency DEA. Social network analysis is conducted and eigenvector centrality values are used as the weights to compute the superefficiency score weighted by eigenvectorcentralitys. A final aggregation of the results is also provided to specify the top airline company. Finally, conclusions and further suggestions are given.

2. Literature review

2.1. Airline company efficiency research methods

The performance of airline companies has attracted the attention of the researchers. Different methods, such as Stochastic Frontier, DEA, Multi-Criteria Decision-Making methods (MCDM), regression, tobit, logit, etc., are used for this purpose. However, as we will see in the literature survey, the analysis is generally focused on the financial data of these companies, whereas the nonfinancial performance is not usually taken into account (Dinçer et al., 2017).

The first group of studies use MCDM methods for their performance analyses of airline companies. For this purpose, different MCDM methods have been developed to address airline performance evaluation problems (Barros and Wanke, 2015; Wanke et al., 2015; Pineda et al., 2018; Dinçer et al., 2017). The studies apply several MCDM approaches to the problem, compare their results, and then make a final decision. However, this approach is difficult to comprehend and implement because it requires an extensive technical knowledge in MCDM fields (Wang et al., 2016). Additionally, in traditional MCDM approaches, the performance evaluation of the airline industry may require the consideration of qualitative and quantitative data and a large number of performance attribute evaluations. In all these methods, there are main disadvantages that need to be discussed. First, different users will obtain different results when using the same method because often each have different backgrounds, expertise and experience. The preferred information associated with the decision-makers in the evaluation criteria varies from person to person. Additionally, the ratings and weights of the criteria are assumed to be known precisely. However, using different relative criteria weights has a significant effect on the ranking of the alternatives. In fact, the ranking results are very sensitive to changes in the attribute weights. Different techniques may yield different results when applied to the same problem. There are no better or worse techniques, only techniques that fit better to certain situations. It is not easy to say which MCDM approach is more reasonable and reliable for airline performance evaluation problems.

On the other hand, the models based on constructing an efficient frontier allows us to analyze the maximum possible output given certain inputs, and then to calculate the distance of the observed output to that frontier. The mathematical models proposed to determine such a frontier can be broadly classified as parametric models (e.g., stochastic frontier analysis (SFA)) and nonparametric models (e.g., DEA as introduced by Charnes et al. (1978)). In a parametric model, a functional form of the production function needs to be specified, in contrast to a nonparametric model, where specific assumptions about the form of the production function are not necessary. The DEA technique assumes that all deviations from the efficient frontier are due to inefficiency, while the SFA technique assumes that deviations from the efficient frontier can be either a realization of inefficiency or a random shock. There is no consensus as to which the most appropriate technique is. In fact, each has its own strengths and weaknesses (Coli et al., 2011; Barros and Couto, 2013). However, the parametric DEA models have been widely applied to measure the efficiency of airlines. DEA is a method of measuring the relative efficiency of a group of operating units wherein the relative values of the variables are unknown (Chow, 2014; Coli et al., 2011; Barros and Peypoch, 2009).

Most of the DEA studies evaluate the performance of the airlines in a specific country or region DEA (Saranga and Nagpal, 2016; Lee and Worthington, 2014; Lu et al., 2012; Mallikarjun, 2015; Rouse et al., 2002; Saranga and Nagpal 2016; Sakthidharan and Sivaraman, 2018).

Fuzzy DEA is an extended form of the standard DEA application to airlines performance evaluation, and is especially preferred in the case of uncertain data (Wanke et al., 2016; Soltanzadeh and Omrani, 2018)

Recently, there has been a growing interest in applying DEA models to evaluate environmental performance of airlines and to reduce undesirable outputs in addition to evaluating financial performance (Chang et al., 2014, Arjomanbdi and Seufert, 2014, Choi et al., 2015, Cui and Li, 2017a, Li and Cui, 2017, Chen et al., 2017).

Lozano and Gutierrez (2011) introduce a multiobjective DEA approach and Barak and Hadooei (2018) use multiattribute decision making to evaluate airline performance evaluation in order to explore different trade-offs among airline operations, environmental impact, fleet costs and operating costs.

In conventional DEA models used to evaluate the airline efficiencies, the system is considered as a black box and does not take into account different processes of it, each having its own inputs and outputs. However, recently, network DEA models consider the system as composed of several stages with serial structure. Lozano and Gutierrez (2014) use a slack-based network DEA to analyze the efficiency of European airlines. Chen et al. (2017) provide a stochastic network DEA model to assess the efficiency of 13 major Chinese airlines from 2006 to 2014. Zhu (2011) builds a two-stage network DEA process to measure airline performance.

Among the methods used to analyze airline companies' efficiencies, DEA accommodates multiple inputs and outputs, uses linear programming and does not require assumptions about the statistical properties of the variables. DEA does not require the specification of a functional form to be fitted. If the true functional form is unknown, this feature of DEA could be advantageous, since it avoids the danger of fitting the wrong functional form (Retzlaff-Roberts et al., 2004). That is, why a DEA-based efficiency model is used in this study. However, a limitation of DEA methods is that they classify the decision-making units (DMUs) as efficient when they have a 100% efficiency score and inefficient when they score below a 100% efficiency score. Although such a classification allows DEA to evaluate the efficiency of any data set, it does not allow the ranking of the DMUs. Several combinations based on superefficiency and cross-efficiency (Li et al., 2018), social networks (De Blas et al., 2018) and MCDM (Rakhshan, 2017) with data envelopment analysis are used as new ideas to eliminate this problem. Aldamak and Zolfaghari (2017) provide a detailed review of literature related to ranking methods with DEA and comparing their advantages and shortcomings.

The superefficiency concept in DEA was proposed by Andersen and Petersen (1993) as a useful tool when there are too many efficient DMUs under evaluation and it is crucial to rank these efficient DMUs. The core idea of the proposed methodology is to exclude the target DMU from the reference set, which allows a DMU to be located on the efficient frontier. Therefore, the superefficiency score for an efficient DMU can take any value greater than or equal to one (Zarafat Angiz et al. (2013), De Blas et al., 2018)). Later, Tone (2002) extended the superefficiency model of Andersen and Petersen (1993) and established the slacks-based measure of superefficiency, which evaluates efficiency by means of slack variables. Slack variables defined in the model have the following characteristics: They are units-invariant and they represent either input excesses or output shortfalls (Põldaru and Roots, 2014). The earlier literature has pointed out the importance and need for the superefficiency concept in DEA models to provide additional discrimination and ranking power (Ruggireo, 2005; Liu and Lu, 2010).

In this paper, a novel approach combining superefficiency, stepwise regression and social network analysis is used to rank the efficient airline companies according to financial, operational and marketing dimensions. An input-orientation is preferred, since the outputs are less likely to be under the control of the individual airline companies than their choice of inputs in a competitive market. The CCR (Charnes, Cooper and Rhodes) model is also preferred in the published literature on airline efficiency studies (Coli et al., 2011; Rai, 2013; Sakthidharan and Sivaraman, 2018)). Therefore, an input-oriented slacks-based superefficiency DEA model with constant returns to scale (hereinafter Super-SBM-I-C) is preferred in this research.

The justification of selecting Super-SBM-I-C as the most proper for implementation can be justified as follows. The inputs and outputs selected in this study evaluate both operational(Available Seat Kilometer (ASK), Revenue Passenger Kilometer (RPK), Fleet Size, Cargo Carried (Metric Tons), Passenger Carried (PAX), Employee Number, On-Time Departure Performance (OTP)), financial (Debt Ratio, Current Ratio, Quick Ratio, Cash Ratio, Liquidity, Net Profit Margin (NPM)) and service satisfaction (Overall Customer Satisfaction Score (OCSS)). Therefore an overall efficiency is analyzed rather than focusing on only technical efficiency. Such an evaluation is consistent with the majority of existing airline efficiency studies (Sjörgen, 2016). This made CCR model the be the most proper approach because CCR model accepts that if a DMU is efficienct it is both technically and scale efficient while under VRS model a unit efficiency score means only technical efficiency (Kottas and Madas, 2018; Thanassoulis, 2001). On the other hand, airlines have greater control over the inputs while the outputs are primarily influenced by macro-economic factors. We assume that airlines have a higher influence on the input variables than on the output variables. Our aim is to gain efficiency by reducing excess inputs while continuing to operate with the current technology mix (Kottas and Madas, 2018; Merkert and Hensher, 2011). The reason of selecting superefficienct DEA model is its discrimination power among efficiency scores by eliminating ties of efficient DMUs and its potential to detect outliers which consists of the DMUs having superefficiency scores greater than two (Kottas and Madas, 2018).

To the best of our knowledge, there is no published paper combining a network-based approach and superefficiency in DEA to improve the discriminating power of traditional DEA for performance evaluation.

2.2. Research on variable selection in DEA

The specification of a DEA model necessitates the selection of appropriate inputs and outputs to be included in the model. One potential limitation of DEA is its sensitivity to appropriate variable selection. In fact, the DEA scores are affected by the inclusion or exclusion of an input or an output. Although a simple DEA model that contains all the relevant information is generally preferred, there is always the danger of the exclusion of relevant variables, which may result in biased performance measurement. On the other hand, it is also necessary to avoid including irrelevant variables in the model that may result in overfitting. Therefore, one of the most important steps in the application of data envelopment analysis is the selection of appropriate input and output variables.

The literature review reveals many multivariate statistical techniques, such as Efficiency Contribution Measure (ECM), Principal Component Analysis (PCA), regression-based tests and bootstrapping, for the selection of most appropriate variables (inputs/outputs). Nataraja and Johnson (2011) compare these four most-widely used approaches to variable selection in DEA. Efficiency contribution measures consider two DEA formulations, one with the candidate variable and one without it. A binomial statistical test is then used to determine whether the candidate variable is important for the problem at hand (Chen and Johnson, 2010). Principal Component Analysis (Adler and Golany, 2001) is used to reduce the dimensionality of data. In the regression-based test, efficiency is regressed against a set of candidate variables which tests whether they are significant or not (Ruggiero, 2005). Bootstrapping is proposed by Simar and Wilson (2001) to test the relevance of removing input and output variables, as well as the potential for aggregation. The simulation analysis results of Nataraja and Johnson (2011) show that Principal Component's application to DEA has the smallest run time, works with a smaller sample size ($n \leq 25$), while the efficiency contribution measure works well with a low correlation and sample size but is vulnerable dimensionality problems while bootstrapping, has a heavy computational burden and has poor performance. They conclude that the four methods reveal significant differences and, thus, it is necessary to select the best-fit method according to the conditions of the problem at hand.

Because our problem has a relatively small sample size ($n = 45$) and the correlations among the variables are very low (average correlation = 0.179), is robust to the use of CRS or VRS and is easy to implement, in this research we decided to the use regression-based method for the selection of the appropriate input variables. In fact, the basic reason for low correlation is the factor analysis conducted to combine three variables, namely current, quick and cash ratios under the factor that we called "liquidity".

Wagner and Shimshak (2007) use a formal stepwise approach to variable selection. This method drops one variable at a time and uses a nonparametric test for the significance of the dropped variables. The

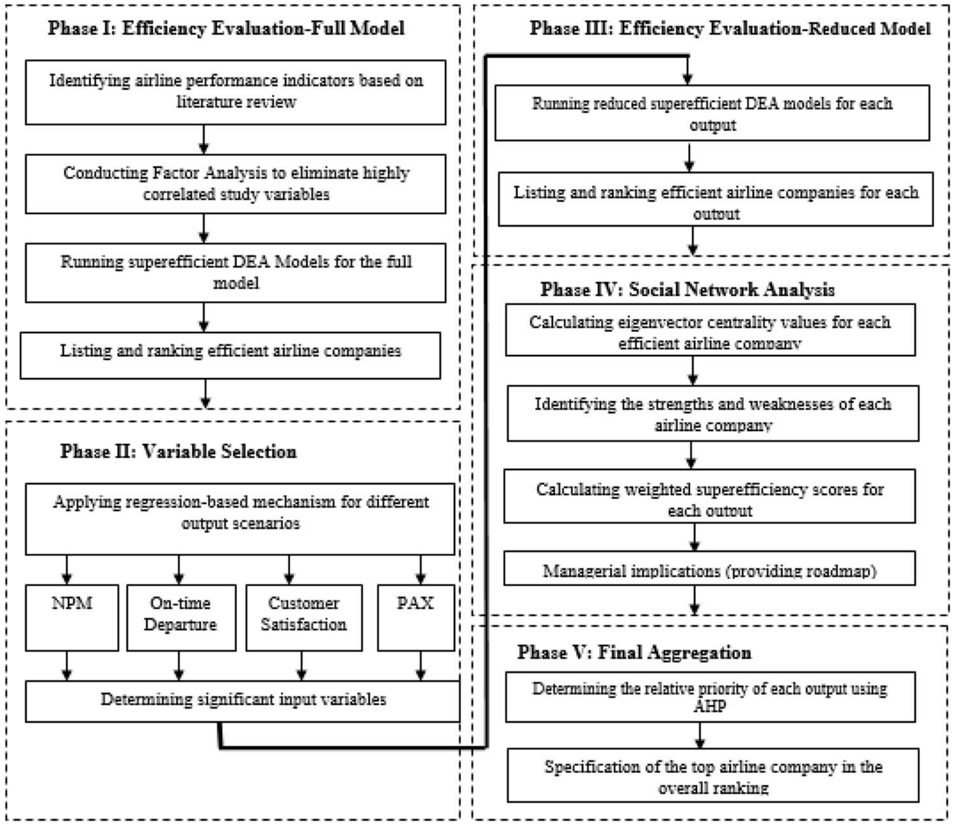

Fig. 1. The flowchart of the proposed model.

method is based on sequentially maximizing (or minimizing) the average change in efficiency as variables are added (dropped) from the model. If more than one variable has a significance value less than 20%, it uses a mean efficiency change and removes the variable with the least significant change. The procedure is repeated until all variables' percentage change in significance values are greater than 20%. At least one input and output variable is required to run the final model.

Subramanyam (2016) proposes a new stepwise method to reduce the data set. The method is based on the improvement of the method proposed by Wagner and Shimshal (2007) and includes an additional step such that, if the percentage change in significance value is greater than 20%, then it retains the variable, otherwise it removes the variable from the data exploration.

In this paper, the stepwise approach proposed by Subramanyam (2016), which is the improved version of Wagner and Shimshal (2007)'s approach, is used for variable selection and for reducing the insignificant input and output variables. However, as a novel approach, the backward procedure is applied not to the classic but to the superefficiency DEA model because an important problem in the application of DEA for ranking is that usually many DMUs are found to be efficient and are therefore given the efficiency score of one (Cook and Seiford, 2009).

3. Proposed methodology

3.1. Framework

The methodology used in this paper consists of five phases. More specifically, the proposed methodology initially runs the superefficient SBM models with all possible inputs and outputs, based on the literature review. Efficient airlines are listed and ranked at the end of the first stage using the full DEA models. Then, in the second stage, a regression-based mechanism is applied to different output scenarios, which are Net Profit Margin (NPM), On-time departure performance (OTP), Customer Satisfaction (OCSS) and Passengers carried (PAX). In the third stage, reduced superefficient SBM models are run and efficient airlines are determined and ranked. Furthermore, benchmarking and road maps for airlines are provided in the final stage, which includes identification of the strengths and weaknesses of each airline company. Managerial implications are provided for the managers of the airline companies for each output. The best airline company as a result of the aggregation of the four outputs is also analyzed through the pairwise comparison of the relative weights of the outputs according to expert opinions. The flowchart of the proposed model is presented in Fig. 1.

3.2. Evaluation of airline companies using proposed framework

3.2.1. Phase I: efficiency evaluation of the full DEA model

The preliminary list of financial, operational and marketing performance indicators based on the literature survey and factor analysis results is given in Table 1. The Bloomberg database (Bloomberg (2016)) is initially used, especially for financial and operational indicators, and the missing values in the data set are obtained from the annual reports of the airline companies. Even though it is difficult to collect consistent data on airline service quality, service quality indicators should be incorporated into airline efficiency studies to make the results more realistic (Oum et al., 2005). In this context, an Overall Customer Satisfaction Score is created using data that was obtained from Skytrax Internet-based surveys that measure the level of customer satisfaction with the airlines. Skytrax sets out this list using the results of airline customer satisfaction surveys and publishes it on their webpage (https://www.airlinequality.com). This is used as a proxy variable for marketing performance. Initially, the Airlines in the Skytrax Top 100 Airlines list of 2016 are used to create the dataset but, due to the lack of data for each airline, the complete and accurate data for 2016 is found for only 45 airlines, which are selected for analysis. The inputs and outputs that are initially are selected for this study based on the most frequently used ones in the

Table 1
Performance indicators used in the analysis.

Classification	Indicator	Evaluation Formula/ Definiton	References	Type of Variable
Financial	Debt Ratio	Total Assets/ Total Liabilities	Feng and Wang (2000), Bigliardi and Ivo Dormio (2010), Dinçer et al. (2017)	Input
	Current Ratio	Current Assets/ Current Liabilities	Wang (2008), Dinçer et al. (2017)	Input
	Quick Ratio	(Cash and Cash Equivalents + Account Receivables + Short Term Investments)/ Short Term Liabilities	Mahesh and Prasad (2012), Lee and Jang (2007), Wang (2008)	Input
	Cash Ratio	Cash and Cash Equivalents/ Short Term Liabilities	Wang (2008), Armen (2013)	Input
	Liquidity	The variable obtained by saving the factor score as a regression score obtained as a result of Principle Component Analysis using Current, Quick and Cash ratios	Lee and Jang (2007)	Input
	Net Profit Margin (NPM)	Net Profit/ Revenue	Teker et al. (2016)	Output
Operational	Available Seat Kilometer (ASK)	Number of Seats Available x Number of Kilometers Flown	Coli et al. (2011), Choi et al. (2015), Saranga and Nagpal (2016)	Input
	Revenue Passenger Kilometer (RPK)	Number of Revenue Passengers x Number of Kilometers Flown	Barros and Peyboch (2009)	Input
	Fleet Size	Number of Aircraft Operated by Airline	Barros and Peyboch (2009)	Input
	Cargo Carried (Metric Tons)	Payload Carried by Airline	Sakthidharan &Sivaraman (2018)	Output
	Passenger Carried (PAX) (Million)	Passenger Carried by Airline	Sakthidharan &Sivaraman (2018)	Output
	Employee Number	Number of Employee	Barros and Peyboch (2009), Ha et al., 2013, Arjomandi and Seufert (2014), Chang et al. (2014), Lee and Worthington (2014), Choi et al. (2015), Cui and Li, 2017	Input
	On-Time Departure Performance (OTP) (%)	Ratio of Departure within +-15 Minutes of Scheduling Departure Time	see https://www.oag.com/airport-and-airline-on-time performance-report), Cho and Lee (2011), Chow (2014), Zhang et al. (2014), Dinçer et al. (2017)	Output
Marketing	Overall Customer Satisfaction Score (OCSS)	The Ratings of Airlines Between 1 and 10 about Airlines Overall Service Quality	see https://skytraxratings.com Chow (2014)	Output

publihed literature. Data availability is also considered. However, in the second step most significant inputs are screened by step-wise regression analysis.

As can be seen from Table 1, we have several financial ratio indicators in this research. It is known that the convexity axiom embedded in standard DEA models cannot be fully satisfied where the dataset includes ratio measures and the results obtained from such models may not be correct and reliable (Zhu, 2011; Hatami-Marbini and Toloo, 2019). Hollingsworth and Smith (2003) stated that BCC formulation should be deployed when rations are used in DEA. This specification ensures that all comparison between units is by interpolation only, and that extrapolation of behaviour to infeasible performance is ruled out. However, the reasons of using specifically a CRS based model in this study is explained in detail in section 2.1. In order to avoid the ratio issue to some degree, a factor analysis is conducted by taking the logarithm of both the numerator and the denominator of each ratio. In fact, when the information provided by the Cash, Current and Quick Ratios variables are considered, it can be seen that all of these variables are indicators of the cash availability of companies and, hence, they provide the same type of information. Therefore, Factor Analysis results obtained after the logarithmic transformation of the numerator and denominator of each of these three ratio variables can be seen in Table 2. According to the Factor Analysis result, one dimension, which we call "Liquidity", can explain approximately 96.4% of the variances of Cash, Quick and Current Ratios (see Table 2). For this reason, the Liquidity dimension is used as a variable that can serve as a substitute for these three variables at the subsequent stages., factor analysis is conducted by taking the logarithm of the numerator and denominator of each ratio.

Additionally, we checked whether the number of DMUs (Airlines) is at least twice the total number of input and output factors (Golan et al., 1989). When the number of inputs and outputs of the models are considered, the Full Model has 5 inputs and 6 outputs. Reduced Models 1, 2 and 4 have 3 inputs and 1 outputs, while Reduced Model 3 has just 1 input and 1 output. Therefore, it can be said that the condition is satisfied.

Initially, efficiency evaluations of 45 airline companies using a conventional input-oriented CRS DEA model are carried out. According to the results, 28 of the evaluated (target) airlines are found to be efficient. Because this is a very high number, in order to better discriminate among airline companies, it is decided to use the superefficiency concept. In this study, efficiency evaluations of full and reduced DEA models are conducted using super SBM-I-C. For an efficient DMU_k, super SBM-I-C is formulated as follow (Tone, 2002; Tran et al., 2019):

$$\min \delta_k = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{ik}}}{\frac{1}{s}\sum_{r=1}^{s}\frac{\bar{y}_r}{y_{rk}}},$$

$$\text{s.t. } \tilde{x}_i \geq \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j, \quad i = 1, \ldots, m,$$

$$\tilde{y}_r \leq \sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j, \quad r = 1, \ldots, s, \tag{1}$$

$$\tilde{x}_i \geq x_{ik}, \quad i = 1, \ldots, m,$$

$$0 \leq \tilde{y}_r \leq y_{rk}, \quad r = 1, \ldots, s,$$

$$\lambda_j \geq 0, \quad j = 1, \ldots, n, j \neq k,$$

where $\tilde{x}_i$ $(i = 1, \ldots, m)$ and $\tilde{y}_r$ $(r = 1, \ldots, s)$are decision variables with respect to inputs and outputs, respectively; and λ is a non-negative vector.

Table 3 shows efficient airlines and their superefficiency scores with respect to the full model.

3.2.2. Phase II: the best input and output combination selection using a stepwise regression-based approach

In this study, we employed a stepwise regression-based backward analysis for variable selection. Stepwise regression conducts multiple regression a number of times, each time removing the weakest correlated variable from the model. Based on the literature survey, we determined six important outputs from the available data set, namely cargo carried (CARGO), passenger carried (PAX) and on-time departure, Overall Customer Satisfaction Score (OCSS), Net Profit Margin (NPM) and Revenue per passenger (RPK), for the regression analysis, as these are the most critical outputs for airline companies. However, since no significant inputs remained for CARGO and RPK after the stepwise analysis, they are excluded from the analysis. The stepwise regression analysis is used for each of the 4 outputs separately (reduced models 1,2,3, and 4). In this research, the methodology proposed by Subramanyam (2016) is adapted to the superefficiency model. It iterates through the following steps using the efficiency scores obtained from super SBM-I-C model as dependent variables for each specified output:

Step 1: Determine input variables that contribute the most to predicting the specified output variable.
Step 2: Run the super SBM-I-C model and store the superefficiency scores and add them to the regression model.
Step 3: Check the p-values of all input variables in the model. Remove the inputs from the model if their p-values are above 0.10 (significance test of the dropped variables).
Step 4: Repeat this procedure until all "significant" inputs are in the model and all "nonsignificant" inputs are removed). If the p-value of none of the input variable is significant, the related output-based model is eliminated from consideration

The variables having significant coefficients for each output variable, as well as their standard errors, can be seen in Table 4. As seen from the table, the inputs have negative coefficients.

3.2.3. Phase III: efficiency evaluation of the reduced DEA models

In this phase, the efficient airlines are found using four reduced models, one for each of the four different outputs. The output of Reduced Model 1 is NPM, and the output of the Reduced Model 2 is OTP, while both models have same inputs. Norwegian Airlines, Bangkok Airways, Aegean Airlines, Aeromexico, United Airlines, Icelandair and China Eastern are efficient airlines with respect to both Reduced Models 1 and 2. Alaska Airlines and Copa Airlines have superefficiency scores greater than 1 with respect to only Reduced Model 1. South African Airlines and TAP Air Portugal are efficient according to Reduced Model 2 only. Vietnam Airlines shows high performance with respect to Reduced Model 1 and Reduced Model 3; Delta Airlines is efficient with respect to Reduced Model 1 and Reduced Model 4; and Thai Airways, EasyJet and Asiana Airlines have superefficiency scores greater than 1 according to Reduced Model 4. Table 5 shows the efficient airlines according to the reduced models.

When Table 5 is analyzed, it can be seen that airlines have different superefficiency scores according to the models. Therefore, in order to specify how airlines' superefficiency scores, change with regard to the models used, the coefficients of variations (CV) are calculated. Since CV represents the average superefficiency score variation for each airline, it can be said that the airlines that have CV over 1, such as Thai Airways (1.24), United Airlines (1.19), South African Airways (1.11), Singapore Airlines 1.09), Emirates (1.08), Korean Air (1.07) and China Airlines (1.04), have different superefficiency scores with respect to different models. On the other hand, airlines such as Jet Airways (0.58), Air China (0.57), China Eastern (0.57), TAP Air Portugal (0.45) and Aeromexico (0.44) have approximately 0.5 CV, and this CV indicates that these airlines show nearly the same performance from one model to another. Finally, the overall CV mean is approximately 0.78, and this means that the airlines have approximately 0.8 standard deviation difference in superefficiency scores with respect to the full and reduced models.

As seen from the results even though the reduced models have lower number of efficient airline companies, the discriminatory power of the ranking of superefficiency models is still low, except in reduced model 3. In the full model, which includes all the inputs and outputs, 28 airline companies out of 45 are found to be efficient. In the Reduced Model 1 (Inputs: Debt Ratio, Liquidity, ASK, Output: NPM) the number of efficient airline companies decreased to 11. In Reduced Model 2 (Inputs: Debt Ratio, Liquidity, ASK, Output: OTD) the number of efficient airline

Table 2
Factor analysis result.

	Liquidity
Quick Ratio	0.991
Cash Ratio	0.983
Current Ratio	0.972
Eigenvalue	2.893
% of Variance	96.432

Table 3
Efficient Airlines and their Superefficiency Scores with respect to Full Model.

DMU	Superefficiency Score	Rank	DMU	Superefficiency Score	Rank	DMU	Superefficiency Score	Rank
Thai Airways	5.994	1	Asiana Airlines	1.270	11	China Airlines	1.091	21
United Airlines	3.550	2	Emirates	1.267	12	China Eastern	1.087	22
Vietnam Airlines	3.456	3	TAP Air Portugal	1.250	13	Lufthansa	1.082	23
Norwegian	3.095	4	Singapore Airlines	1.248	14	SAS Scandinavian	1.054	24
Bangkok Airways	1.722	5	Japan Airlines	1.168	15	Alaska Airlines	1.045	25
Delta Air Lines	1.699	6	South African Airways	1.149	16	Copa Airlines	1.039	26
Aegean Airlines	1.592	7	Aeromexico	1.148	17	Southwest Airlines	1.023	27
Korean Air	1.320	8	China Southern	1.121	18	British Airways	1.006	28
Icelandair	1.298	9	Hainan Airlines	1.117	19			
EasyJet	1.273	10	Hawaiian Airlines	1.094	20			

Table 4
Specification of significant input variables for reduced models 1–4 using stepwise regression analysis.

Variables	Unstandardized Coefficient	Coefficients Standard Error	Significance (t)	Significance (F)
Reduced Model 1:				0.002**
NPM (Dependent output)				
Constant	1.854	0.346	0.000***	
Employee Number (Input)			0.727	
Debt Ratio (Input)	−0.015	0.004	0.001***	
Liquidity (Input)	−0.186	0.078	0.021**	
Available Seat Kilometer (Input)	−2.03E-06	0.000	0.005***	
Fleet Size (Input)			0.631	
Reduced Model 2				0.004**
OTP (Dependent-Output)				
Constant	1.884	0.390	0.000***	
Employee Number (Input)			0.309	
Debt Ratio (Input)	−0.009	0.005	0.067*	
Liquidity (Input)	−0.227	0.088	0.013**	
Available Seat Kilometer (Input)	−2.88E-06	0.000	0.001***	
Fleet Size (Input)			0.300	
Reduced Model 3				0.001**
OCSS (Dependent-Output)				
Constant	0.912	0.104	0.000***	
Employee Number (Input)			0.271	
Debt Ratio (Input)			0.898	
Liquidity (Input)			0.131	
Available Seat Kilometer (Input)	−2.44E-06	0.000	0.001***	
Fleet Size (Input)			0.220	
Reduced Model 4				0.039**
PAX (Dependent-Output)				
Constant	1.090	0.229	0.000***	
Employee Number (Input)	−8.92E-06	0.000	0.064*	
Debt Ratio (Input)			0.127	
Liquidity (Input)	−0.174	0.073	0.022**	
Available Seat Kilometer (Input)			0.688	
Fleet Size (Input)	−0.001	0.001	0.071*	

* Significant at the 0.10 level (2-tailed).
** Significant at the 0.05 level (2-tailed).
*** Significant at the 0.01 level (2-tailed).

companies decreased to 9, and in Reduced Model 3 (ASK is the input, OCSS is the output), only one airline remained and, finally, in Reduced Model 4 (Inputs: Fleet, Liquidity, Employee; Output: PAX), the number of efficient airline companies is 4 (see Table 5). As a result, in order to better discriminate among the efficient airline companies and to specify their strength and weaknesses for each reduced model, in the next stage, a social network-based analysis is conducted.

3.2.4. Phase IV: social network-based superefficiency DEA analysis to provide a roadmap

In the fourth phase (Benchmarking), Social Network Analysis is used to identify the importance of each airline company within the network. Social Network Analysis has emerged as a key concept for focusing on the relationships between social entities such as nations, families, etc. These entities are influenced by other entities they take as role models, and such connections often comprise a social network and can be analyzed using social network analysis methods (DeNooy et al., 2011; McCulloh et al., 2013).

In this paper, the social entities are the airline companies. The use of social networks in airline management is a very recent trend. To our knowledge, there are very few papers that use social networks in airline management. Çavdar and Ferhatosmanoğlu (2018) analyzes the customer lifetime value in airline management while Lozano and Calzada-Infante (2017, 2019) use it for benchmarking and efficiency assessment of airlines.

In this research, an eigenvector centrality measure is used to define the weights of the superefficiency scores of the efficient airlines and to calculate the weighted average score for each to have a robust discrimination in terms of ranking the efficient companies. Furthermore, we determined the strengths and weaknesses of each efficient airline company for each of the reduced models corresponding to each output. The network-based eigenvector centrality method proposed by Liu and Lu, 2010 is used for this purpose. Finally, the managerial implications are given for the airlines to improve their efficiency in terms of each reduced model.

In the recent large-group decision-making literature, the centrality concept of social networks is used as the weight of the social entities to show their relative importance (Hengie et al. (2018); Lesser et al. (2017); Dong et al. (2018)). In fact, the degree of centrality counts how many links each airline company has. The degree of an airline is simply the count of the number of links going into it, in-degree, or coming from it, out-degree. However, degree centrality is limiting because it does not take into account which other nodes are important in the network. In this paper, we would such as to know the number of connections among superefficient airline companies. Therefore, it is necessary to find which airline companies are connected to important airline companies (i.e., airline companies with many links). The airline companies with high eigenvector values have the power to connect with many other influential airline companies. This measure is called eigenvector centrality. In this paper, the eigenvector centrality measure is used to find the relative weight of each airline company for each output and the related significant input combination. The vectors are created by the Pajek64 5.05 Network > Create Vector > Centrality > Hubs-Authorities command, which contains eigenvector centrality scores (De Nooy et al., 2011). As in degree centrality, eigenvector centrality measure assumes that, if decision-making units are more central, that is if they have many central contacts, it is important to know if they play a role in influential decision-making units. In other words, it is important to be a role model but it is also important to know for which airline you are acting as a role model (Liu and Lu (2010), De Nooy et al., 2011),). If an airline company

Table 5
Airline Companies' efficiency scores according to the Reduced Models.

Rank	Reduced Model 1	Reduced Model 2	Reduced Model 3	Reduced Model 4
1	Norwegian (2.042)	Norwegian (2.270)	Vietnam Airlines (1.062)	Thai Airways (4.280)
2	Bangkok Airways (1.236)	Aegean Airlines (1.431)	Aeromexico (0.940)	Delta Air Lines (1.254)
3	Vietnam Airlines (1.124)	Bangkok Airways (1.117)	TAP Air Portugal (0.876)	easyJet (1.209)
4	Aegean Airlines (1.122)	China Eastern (1.114)	Bangkok Airways (0.083)	Asiana Airlines (1.125)
5	Aeromexico (1.112)	Aeromexico (1.097)	Aegean Airlines (0.031)	Southwest Airlines (0.833)
6	United Airlines (1.088)	TAP Air Portugal (1.080)	Icelandair (0.027)	China Eastern (0.829)
7	Icelandair (1.077)	Icelandair (1.071)	Hawaiian Airlines (0.020)	Norwegian (0.811)
8	Delta Air Lines (1.077)	United Airlines (1.046)	Copa Airlines (0.017)	China Southern (0.779)
9	Alaska Airlines (1.052)	South African Airways (1.004)	Finnair (0.011)	Hainan Airlines (0.732)
10	China Eastern (1.031)	Vietnam Airlines (0.926)	Air New Zealand (0.010)	American Airlines (0.727)
11	Copa Airlines (1.017)	Hawaiian Airlines (0.877)	Asiana Airlines (0.010)	Air China (0.695)
12	Hawaiian Airlines (0.903)	Avianca (0.679)	EVA Air (0.010)	Turkish Airlines (0.669)
13	Japan Airlines (0.825)	Copa Airlines (0.676)	China Airlines (0.009)	Qantas Airways (0.649)
14	Air China (0.659)	Jet Airways (0.659)	Garuda Indonesia (0.008)	Emirates (0.638)
15	Air New Zealand (0.590)	Alaska Airlines (0.642)	Alaska Airlines (0.008)	KLM (0.626)
16	China Southern (0.587)	China Airlines (0.638)	South African Airways (0.008)	Air France (0.626)
17	easyJet (0.580)	Air China (0.635)	Avianca (0.008)	Lufthansa (0.577)
18	TAP Air Portugal (0.577)	SAS Scandinavian (0.621)	Virgin Australia (0.008)	Jet Airways (0.541)
19	Southwest Airlines (0.548)	Garuda Indonesia (0.609)	SAS Scandinavian (0.007)	Korean Air (0.515)
20	British Airways (0.503)	Asiana Airlines (0.599)	Korean Air (0.006)	Garuda Indonesia (0.508)
21	Hainan Airlines (0.473)	Virgin Australia (0.594)	Norwegian (0.006)	SAS Scandinavian (0.490)
22	Jet Airways (0.460)	Air New Zealand (0.581)	Jet Airways (0.005)	British Airways (0.457)
23	Qantas Airways (0.439)	Finnair (0.569)	Japan Airlines (0.005)	Aeroflot (0.451)
24	SAS Scandinavian (0.426)	China Southern (0.561)	Hainan Airlines (0.005)	Avianca (0.444)
25	Aeroflot (0.420)	Korean Air (0.526)	Thai Airways (0.005)	Vietnam Airlines (0.443)
26	Asiana Airlines (0.417)	Thai Airways (0.486)	easyJet (0.004)	Cathay Pacific (0.430)
27	Air Canada (0.406)	Qantas Airways (0.445)	ANA All Nippon Airways (0.004)	Virgin Australia (0.423)
28	Finnair (0.397)	EVA Air (0.444)	Air Canada (0.003)	ANA All Nippon Airways (0.404)
29	ANA All Nippon Airways (0.346)	Japan Airlines (0.392)	Singapore Airlines (0.003)	Air Canada (0.404)
30	American Airlines (0.318)	easyJet (0.387)	Cathay Pacific (0.003)	Alaska Airlines (0.382)
31	Avianca (0.315)	Delta Air Lines (0.383)	Qantas Airways (0.002)	Aegean Airlines (0.380)
32	EVA Air (0.293)	Aeroflot (0.363)	Aeroflot (0.002)	Japan Airlines (0.366)
33	Lufthansa (0.286)	Singapore Airlines (0.345)	Southwest Airlines (0.002)	Hawaiian Airlines (0.353)
34	China Airlines (0.284)	Southwest Airlines (0.344)	Turkish Airlines (0.002)	TAP Air Portugal (0.324)
35	Thai Airways (0.273)	ANA All Nippon Airways (0.332)	China Southern (0.002)	Singapore Airlines (0.314)
36	Garuda Indonesia (0.272)	Turkish Airlines (0.321)	British Airways (0.001)	Air New Zealand (0.311)
37	Singapore Airlines (0.261)	Air Canada (0.315)	Lufthansa (0.001)	Finnair (0.302)
38	KLM (0.229)	Cathay Pacific (0.295)	China Eastern (0.001)	Bangkok Airways (0.279)
39	Air France (0.229)	British Airways (0.289)	KLM (0.001)	Copa Airlines (0.264)
40	Emirates (0.182)	Air France (0.286)	Delta Air Lines (0.001)	South African Airways (0.230)
41	Turkish Airlines (0.176)	KLM (0.286)	Air France (0.001)	Icelandair (0.222)
42	Cathay Pacific (0.170)	Hainan Airlines (0.271)	Air China (0.001)	EVA Air (0.221)
43	Virgin Australia (0.072)	Lufthansa (0.266)	Emirates (0.001)	United Airlines (0.205)
44	Korean Air (0.068)	American Airlines (0.258)	United Airlines (0.000)	Aeromexico (0.198)
45	South African Airways (0.052)	Emirates (0.248)	American Airlines (0.000)	China Airlines (0.099)

acts as a role model to other influential airline companies, then it is more likely to exert influence through them. An airline company with high eigenvector centrality is connected to many other nodes that are themselves well-connected. Because of their connectedness to other well-connected airline companies, such companies are expected to be influential nodes in the network.

After the calculation of eigenvector centrality, the superefficient airline companies are ranked in a more robust way by multiplying their superefficiency score coming from the superefficient DEA model by their corresponding normalized eigenvector centrality value obtained in the previous step. The process is repeated for each reduced model except reduced model 3, where the efficient airline company was already reduced to one. Additionally, the network-based eigenvector concept suggested by Liu and Lu, 2010 is also used to develop a performance map to point out strengths and weaknesses of the ranked superefficient airline companies. Relative strengths and weaknesses of the superefficient airline companies cross-organizations and within-organization can be calculated by the following formulas (2–9):

Step 1: Transform all DEA results into a directed and weighted network where each node represents a DMU (airline company) and the link between a pair of node represents the referencing relationship between the pair. The corresponding lambda value, λ_{jk} gives information about the endorsement of inefficient airline to the efficient airline. For example, if an airline *j* is an exemplar of airline *k* and the corresponding lambda value, λ_{jk} pointing from node *k* to node *j* can be generated.

Step 2: Calculate efficiency scores of all airlines using Super-SBM-I-C model. The value of λ_{jk}^{t} indicates the contribution of the *ith* input of

Table 6
Ranking of the Efficient Airline Companies and their Strengths and Weaknesses for the Reduced Model 1 (Output: NPM).

Super-SBM-I-C Rank	Superefficiency Score	Eigenvector centrality value (Weight)	Normalized Weights	Superefficiency score weighted by eigenvector centrality	Rank of airlines based on superefficiency score weighted by eigenvector centrality(5)	Strengths	Weaknesses
(1)	(2)	(3)	(4)=(3)/SUM (3))	(5)=(2)*(4)	(6)	(7)	(8)
3	1.124	0.260	0.167	0.527	Vietnam Airlines	ASK (0.524), Liquidity (0.462)	Debt (0.015)
7	1.077	0.218	0.167	0.505	Icelandair	ASK (0.450), Debt (0.450)	
11	1.017	0.066	0.168	0.479	Copa Airlines	ASK (0.348), Debt (0.305), Liquidity (0.348)	
10	1.031	0.471	0.136	0.394	China Eastern		ASK (0.001)
5	1.112	0.468	0.092	0.289	Aeromexico	ASK (0.968)	Debt (0.022), Liquidity (0.011)
1	2.042	0.382	0.046	0.264	Norwegian	Liquidity (0.353)	
9	1.052	0.209	0.078	0.230	Alaska Airlines	ASK (0.483), Liquidity (0.483)	Debt (0.034)
8	1.077	0.116	0.074	0.225	Delta Airlines	Liquidity (0.555)	
4	1.122	0.129	0.041	0.130	Aegean Airlines	ASK (0.5), Debt (0.500)	Liquidity (0.000)
2	1.236	0.021	0.024	0.082	Bangkok Airways	ASK (0.499), Debt (0.499)	Liquidity (0.002)
6	1.088	0.469	0.008	0.023	United Airlines	Debt (0.985)	ASK (0.007), Liquidity (0.008)

Strengths and Weaknesses columns represents the factors with IO^{j}_{p} greater than or equal to 0.2 (strengths) and less or equal to 0.05 (weaknesses) (Liu and Lu, 2010).

the *kth* airline to the *jth*airline in the reference set under DEA specification *t*.

Step 3: Normalize the lambda value. The contribution of the *ith* input of the *kth* airline to the *jth*airline in the reference set under DEA specification *t* can be rescaled as follows:

$$IW_{ij}^{t,k} = \frac{\lambda_{jk}^{t} x_{ij}^{t}}{\sum_{j\in E} \lambda_{jk}^{t} x_{ij}^{t}}, 0 < IW_{ij}^{t,k} \leq 1. \tag{2}$$

Similarly, the contribution of the *rth* output of the *kth* airline to the *jth*airline in the reference set under DEA specification *t* can be rescaled as follows:

$$OW_{rj}^{t,k} = \frac{\lambda_{jk}^{t} y_{rj}^{t}}{\sum_{j\in E} \lambda_{jk}^{t} y_{rj}^{t}}, 0 < OW_{rj}^{t,k} \leq 1. \tag{3}$$

In the reference set under DEA specification *t*, the overall contribution of the *kth* airline to the *jth*airline can be computed as follows:

$$IOW_{jk}^{t} = \frac{1}{(m+s)} \left(\sum_{i=1}^{m} IW_{ij}^{t,k} + \sum_{r=1}^{s} OW_{rj}^{t,k} \right) \tag{4}$$

Step 4: Aggregate results of all DEA specifications onto one network to obtain the following adjacency matrix *A*.

$$A = \left[\sum_{t=1}^{w} IOW_{jk}^{t} \right] \tag{5}$$

where A is a square matrix of order n and w is the total number of DEA specifications $w = (2^m - 1)(2^s - 1)$.

Step 5: Calculate the eigenvector centrality value for each network node (airline).

Step 6: Rank airlines according to obtained eigenvector centrality value (in Step 5) in descending order.

***Sensitivity of the airline performance to individual input and output variables. Ranking the airline companies under each input or output variable.**

$$A = \frac{1}{m+s} \left(\sum_{i=1}^{m} AI_i + \sum_{r=1}^{s} AO_r \right), \tag{6}$$

where,

$$AI_i = \left[\sum_{t=1}^{w} IW_{ij}^{t,k} \right], i = 1, 2, \ldots, m,$$

$$AO_r = \left[\sum_{t=1}^{w} OW_{rj}^{t,k} \right], r = 1, 2, \ldots, s. \tag{7}$$

In this formulation, AI_i and AO_i are square matrices of order n. Each entry in these matrices denote the aggregated endorsement of the *kth* airline to the *jth* airline in the reference set through the *ith* input, and the endorsement of the *kth*airline to the *jth* airline in the reference set through the *rth* output, respectively. AI_i and AO_i can be treated as network adjacency matrices and airlines can be ranked in descending order according to obtained eigenvector centrality value under each input or output variable.

***Within organization strengths and weaknesses among all variables for an airline:**

The endorsement from all peers over all specifications to an efficient airline *j* through a specific input/output *p* can be calculated as follows:

$$IOWS_j^p = \left\{ \begin{array}{l} \sum_{k=1}^{n} \sum_{t=1}^{w} IW_{ij}^{t,k},\ p = i, i = 1, 2, \ldots, m,\ \text{ve} \\ \sum_{k=1}^{n} \sum_{t=1}^{w} OW_{rj}^{t,k}, p = m + r, r = 1, 2, \ldots, s. \end{array} \right\} \tag{8}$$

where *p* is a consolidated input/output index. The relative importance of each input/output factor *p* to an efficient airline equals:

$$IO_j^p = \frac{\left(IOWS_j^p\right)^2}{\sum_{p=1}^{m+s} \left(IOWS_j^p\right)^2} \tag{9}$$

Table 7
Ranking of the Efficient Airline Companies and their Strengths and Weaknesses for Reduced Model 2 (Output: OTP).

Super-SBM-I-C Rank	Superefficiency Score	Eigenvector centrality value (Weight)	Normalized Weights	Superefficiency score weighted by eigenvector centrality	Rank of airlines based on superefficiency score weighted by eigenvector centrality(5)	Strengths	Weaknesses
(1)	(2)	(3)	(4)=(3)/SUM (3))	(5)=(2)*(4)	(6)	(7)	(8)
1	2.270	0.460	0.187	0.426	Norwegian	Liquidity (0.386)	
4	1.114	0.461	0.188	0.209	China Eastern	Liquidity (0.972)	ASK (0.013), Debt (0.013)
2	1.143	0.353	0.144	0.206	Aegean Airlines	ASK (0.497), Debt (0.497)	Liquidity (0.005)
6	1.080	0.462	0.189	0.203	TAP Air Portugal	ASK (0.698), Liquidity (0.296)	Debt (0.004)
8	1.046	0.462	0.189	0.197	United Airlines	Debt (0.983)	Ask (0.008), Liquidity (0.008)
7	1.071	0.125	0.051	0.054	Icelandair	ASK (0.347), Debt (0.347), Liquidity (0.304)	
9	1.004	0.065	0.026	0.026	South African Airways	ASK (0.500), Liquidity (0.500)	Debt (0.000)
5	1.097	0.049	0.020	0.021	Aeromexico	ASK (0.626), Debt (0.328)	Liquidity (0.004)
3	1.117	0.011	0.004	0.005	Bangkok Airways	ASK (0.500), Debt (0.500)	Liquidity (0.002)

Strengths and Weaknesses columns represents the factors with IO^{j}_{p} greater than or equal to 0.2 (strengths) and less or equal to 0.05 (weaknesses) (Liu and Lu, 2010).

Table 8
Efficiency scores, ranks, strengths and weaknesses for the reduced model 3 (output: OCSS).

Super-SBM-I-C Rank	Superefficiency Score	Eigenvector centrality value (Weight)	Normalized Weights	Superefficiency score weighted by eigenvector centrality	Rank of Airlines based on Superefficiency score weighted by eigenvector centrality
(1)	(2)	(3)	(4)=(3)/SUM (3))	(5)=(2)*(4)	
1	1.062	1	1	1.062	Vietnam Airlines

Table 9
Ranking of the Efficient Airline Companies and their Strengths and Weaknesses for Reduced Model 4 (Output PAX).

Super-SBM-I-C Ran k	Superefficiency Score	Eigenvector centrality value (Weight)	Normalized Weights	Superefficiency score weighted by eigenvector centrality	Rank of airlines based on superefficiency score weighted by eigenvector centrality(5)	Strengths	Weaknesses
(1)	(2)	(3)	(4)=(3)/SUM (3))	(5)=(2)*(4)	(6)	(7)	(8)
1	4.280	0.528	0.269	1.152	Thai Airways	Employee (1.935), Fleet (0.583)	-
2	1.254	0.600	0.305	0.383	Delta Air Lines	Employee (0.463), Fleet (0.439), Liquidity (2.205)	-
3	1.125	0.492	0.250	0.282	Asiana Airlines	Employee (0.254), Fleet (2.529), Liquidity (1.813)	-
4	1.209	0.342	0.174	0.174	Easy Jet	Employee (2.851), Fleet (1.556), Liquidity (2.113)	-

Strengths and Weaknesses columns represents the factors with IOjp greater than or equal to 0.2 (strengths) and less or equal to 0.05 (weaknesses) (Liu and Lu, 2010).

Here, IO_j^p is calculated to indicate the relative importance of each input factor $p$among all inputs within an efficient airline company. Input factors with values greater than or equal to 0.2 are labeled as strengths, while values less than or equal to 0.05 are labeled as weaknesses.

This analysis identifies the airline companies that are particularly efficient in certain input/output factors relative to other airline companies. Identifying strengths and weakness provides managerial insights to airline companies, since it highlights the areas where each airline company needs to improve and should make investments. This is the same as detecting the sensitivity of the airline company's performance to individual input and output factors. This tends to screen out specialized efficient organizations, or in other words, it favors airline organizations that have their strengths evenly spread.

In this study, a total of 22 DEA models are run with all input/output combinations (7 for reduced model 1, 7 for reduced model 2, 1 for reduced model 3, and 7 for reduced model 4). By applying the steps (1–5) to each reduced model, adjacent matrices are constructed to calculate eigenvector centrality values and, hence, to determine the importance of each efficient airline in the network for different output scenarios. Next, by employing formulas (6–9), strong and weak factors among all inputs for each output scenario are determined. Identification of strengths and weaknesses within an airline company provides a

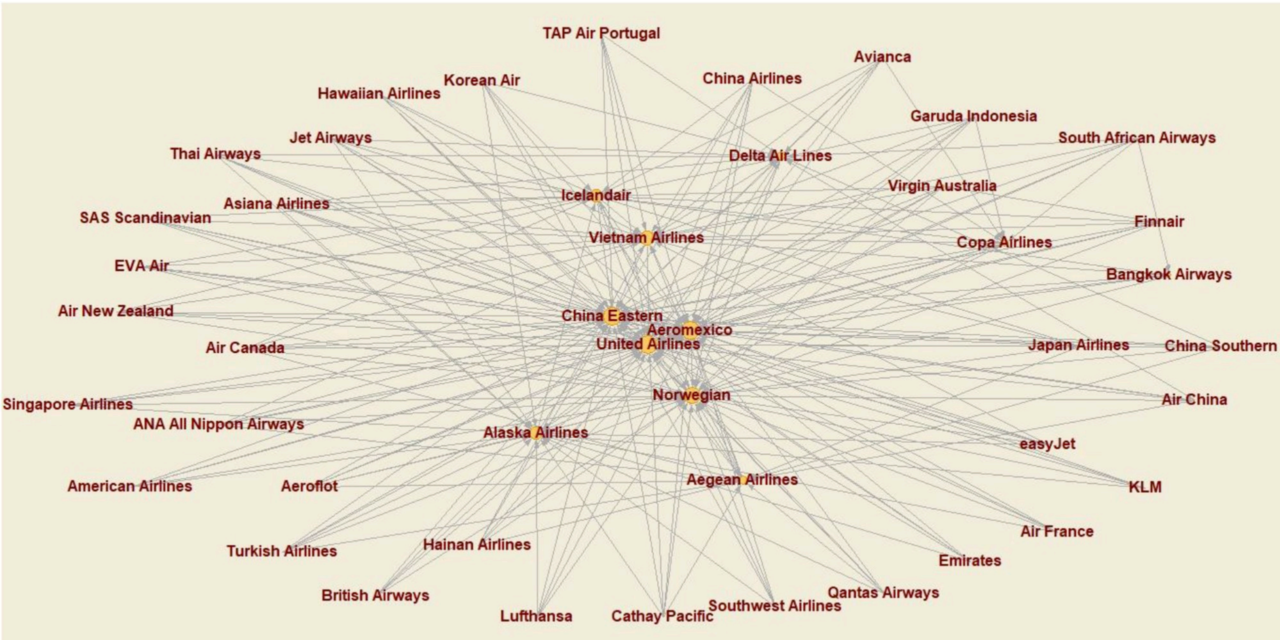

Fig. 2. Reference network of airline companies with respect to Reduced Model 1 (Output: NPM). (The network is plotted with Pajek software using the Kamada-Kawai energy layout option).

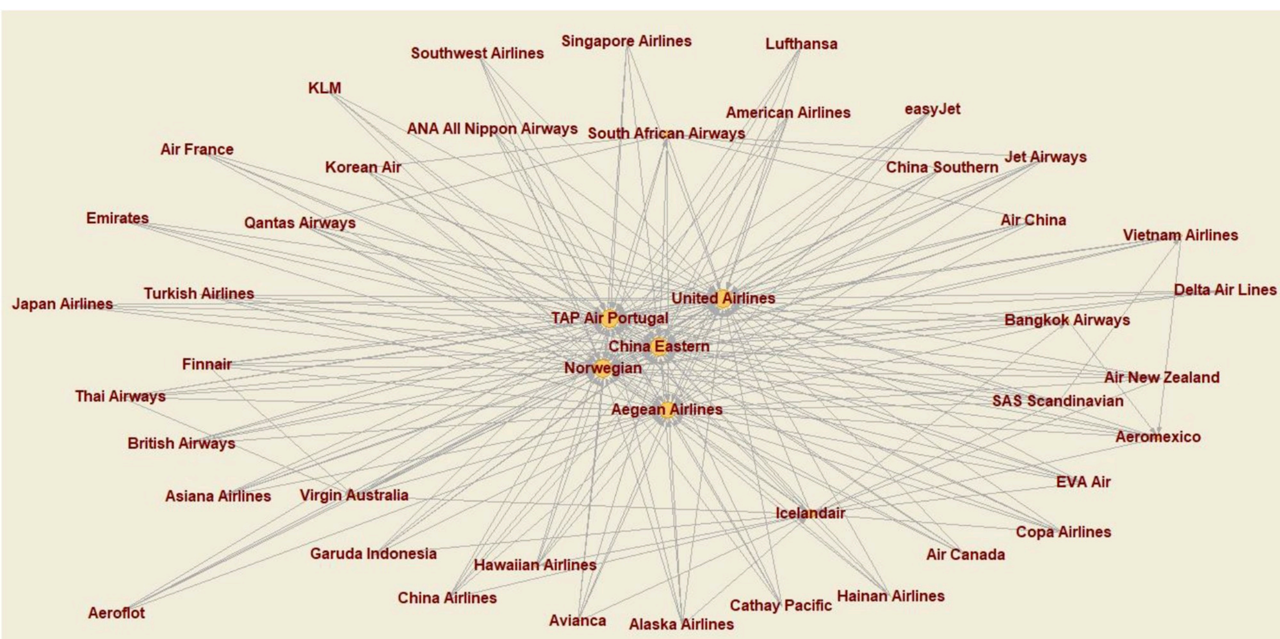

Fig. 3. Reference network of airline companies with respect to Reduced Model 2 (Output:OTP). (The network is plotted with Pajek software using the Kamada-Kawai energy layout option).

roadmap for their improvement. Tables 6–9 presents the rankings of efficient airline companies according to obtained eigenvector centrality values and their strengths and weaknesses within the company for each output scenario in the reduced DEA model.

When Net Profit Margin (NPM) is taken as an output according to the superefficient model, the most superefficient company is Norwegian Airlines (column 1) with its superefficiency value of 2.043. However, it is not the role model endorsed by the most influential airline companies. Fig. 2 shows the role model companies for reduced model 1 at the center.

Because its eigenvector centrality value is low (0.382), when the NPM is selected as output, Norwegian Airlines becomes the sixth most efficient airline in terms of its weighted super efficiency value (0.264). That is, why, with its high eigenvector centrality, the weighted super-efficiency value (0.527) of Vietnam Airlines makes it a leader in terms of NPM. This company has the power to connect with many other influential airline companies outside its immediate connections. In organizational risk terms, it has the ability to form a social elite within the group, building norms and expectations that others in the group will relate to. Vietnam Airlines can improve its debt ratio, its basic strengths are liquidity and available seat kilometers (ASK), while Norwegian Airlines especially outperforms on liquidity (see Table 6). This outcome also shows us that the network-based approach proposed by Liu and Lu,

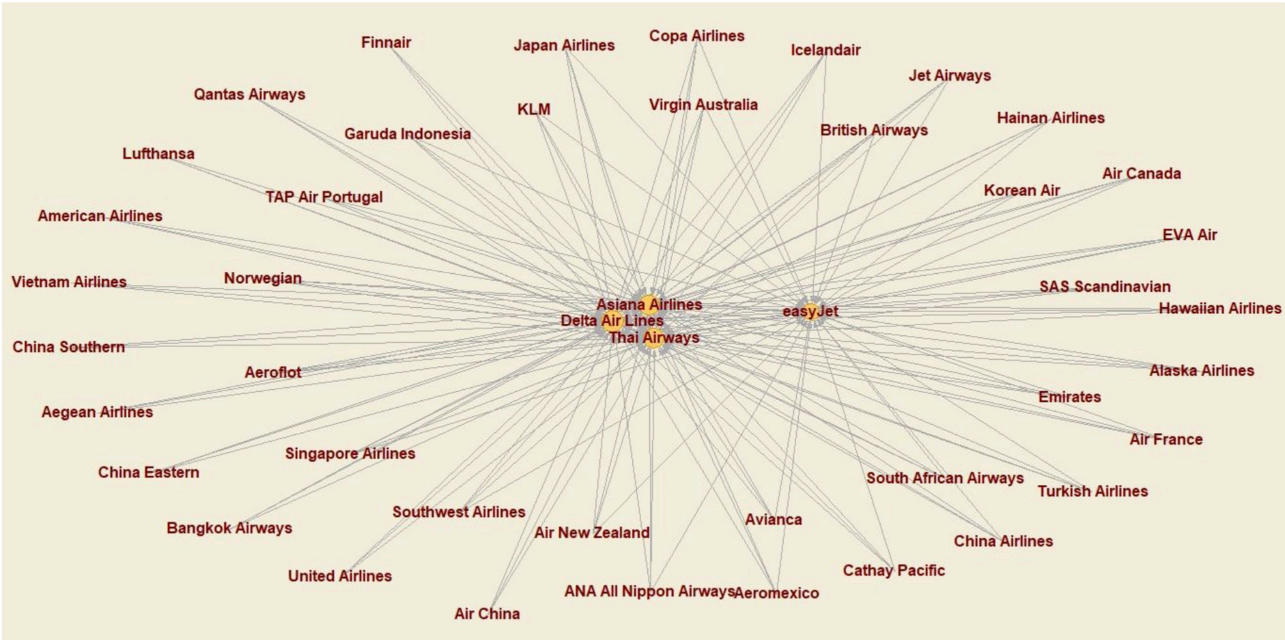

Fig. 4. Reference network of airline companies with respect to Reduced Model 4 (Output:PAX). (The network is plotted with Pajek software using the Kamada-Kawai energy layout option.)

2010 favors organizations that have their strengths evenly spread and tends to screen out specialized efficient organizations.

On the other hand, when On-Time Departure Performance (OTP) is taken as an output, the most superefficient airline is Norwegian Airlines (2.2704) because it has a superefficiency much higher than the rest of the efficient airlines and, hence, has the top superefficiency score weighted by eigenvectorcentrality (see Table 7).

Fig. 3 shows that the eigenvector centrality of United Airlines (0.4624) is the highest. However, because its eigenvector centrality value is also high (0.4603), Norwegian Airline has the highest weighted superefficiency value (0.4266), and this makes it the leader with respect to the OTP dimension.

The greatest strength of Norwegian Airlines is its liquidity and it has no weakness. It influences many other airline companies that are themselves well-connected. The other superefficient airline companies still have some relative weaknesses, such as debt, liquidity and available seat kilometers (ASK). They should take Norwegian Airlines as a role model in these factors.

Because the superefficiency DEA was able to reduce the number of superefficient airline companies to one for reduced model 3, it can be seen that Vietnam Airlines is the leader in terms of overall customer satisfaction and should serve as a dominant role model for the other companies (see Table 8).

Finally, when the efficiency of airline companies is analyzed with respect to passengers carried (PAX), we can see that Thai Airways is the leader in terms of eigenvector centrality (Fig. 4), superefficiency and weighted superefficiency values, and its basic strengths are its fleet and employees (see Table 9).

Fig. 4 shows the airline companies with the highest eigenvector centrality values for reduced model 4 at the center.

To sum up, in Figs. 2–4 efficient airlines which play a role model for the other airlines with respect to each considered output are located at the inner periphery of the network. Size of the related nodes in these figures also provide information about the degree of influence, in terms of Eigenvector centrality. For instance, in Fig. 4, Thai Airways, Delta Air Lines, Asiana Airlines and easyJet are located at the inner cluster since they have the highest eigenvector centrality with respect to output, “PAX”, based on the reference network analysis. Therefore, they should act as role models to the other airlines when we consider output “PAX”. Moreover, Tables 6–9 provide information about within organization strengths and weaknesses of each efficient airline. These tables present only the input factors with greater than or equal to 0.2 (strengths) and less than or equal to 0.05 (weaknesses) due to approach suggested by Liu and Lu (2010). Related to Fig. 4, Table 9 present within organization strengths of these efficient airlines since no weaknesses are observed. To sum up, the strength/weakness of an efficient airline with respect to a certain input exactly varies from one output to another as we can see in Tables 6–9

3.2.5. *Phase V: aggregation*

At the final stage, a pairwise comparison of the four outputs is made by 7 experts from different departments of the airline companies to reflect different perspectives. The relative priorities based on eigenvectors are shown in Table 10 for both the individual evaluations and the group decision (geometric means).

According to the relative priorities calculated in Table 10, financial performance output “Net Profit Margin (NPM)” has the highest priority (0.383), followed by operational performance output “On-time Departure (OTP)” (0.286) and marketing performance output “Overall Customer Satisfaction (OCSS)” (0.273), while passengers carried is

Table 10
Output weights obtained by eigenvectors.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Geometric Mean
NPM	0.3182	0.3125	0.4657	0.4464	0.3076	0.3866	0.4578	0.3791
OTP	0.3182	0.3125	0.2947	0.2373	0.3268	0.3143	0.2074	0.2838
OCSS	0.3220	0.3177	0.1893	0.2250	0.3306	0.2514	0.2921	0.2704
PAX	0.0460	0.0635	0.0560	0.1053	0.0394	0.0522	0.0485	0.0560

Table 11
Overall aggregated scores.

	Output Weights				Superefficiency Score Weighted by Eigenvector Centrality				
Airline	O1	O2	O3	04	Reduced Model 1	Reduced Model 2	Reduced Model 3	Reduced Model 4	Overall Aggregated Score
Vietnam Airlines	0.383	0.287	0.273	0.057	0.527		1.063		0.492
Norwegian					0.264	0.426			0.223
China Eastern					0.394	0.209			0.210
Icelandair					0.505	0.054			0.209
Copa Airlines					0.479				0.183

Note: Reduced Model 1- (O1: NPM); Reduced Model 2 -(O2: OTP); Reduced Model 3 -(O3: OCSS); Reduced Model 4- (O4: PAX).

found to be of the lowest importance (0.056). The weight of each the four output is multiplied by the superefficiency score weighted by eigenvector centrality of each airline for this output and summed in order to get the overall aggregated superefficiency score for each airline. Through this calculation it can be seen that Vietnam Airlines can be accepted as the top airline company, followed by Norwegian Airlines. Overall aggregated scores are presented in Table 11.

4. Conclusions and further suggestions

Superefficiency DEA is an important tool for providing a road map for airline organizations in preparing an efficiency improvement program with the correct allocation of resources. This study examines airline performance models through a five-stage procedure.

Initially, the inputs and outputs used in the literature are evaluated and a factor analysis is conducted to combine Cash, Current and Quick Ratios under one factor that we named “liquidity” because one dimension explains approximately 96.4% of variances among these variables. This resulted in 5 input and 6 output variables. The full superefficiency model developed using all these selected inputs and outputs resulted in 28 superefficient companies, which shows that, in its current state, the developed model does not have a strong power of discrimination in terms of the relative efficiency of the airline companies. That is, why it was decided to specify the significant inputs for each output. As a result, in the second phase, the appropriate selection of inputs and outputs, in which an important issue is getting accurate results related to the performance of the airline company, is carried out using stepwise regression analysis for each output separately. Hence, an important contribution of the research is the use of stepwise regression to select the most significant input combinations to evaluate each output. For this purpose, the methodology proposed by Subramanyam (2016) is applied to the superefficiency case, which is, to our knowledge, a novel application.

Additionally, classic DEA models generally result in many performance leaders and, therefore, discriminating among the DEA results is important. Although the integration of super efficiency with step wise regression permits us to use significant input sets for each output and decreases the number of efficient airline companies for each reduced model, it still suffers from insufficient discriminatory power when there are many performance leaders. This study incorporates social networks into the analysis and uses eigenvector centrality to compute the relative weight of airline companies in terms of their influential power. As a result, a ranking with a much higher discriminatory power is obtained through weighting the superefficiency scores of the airline companies by their eigenvector centrality values (De Nooy et al., 2011).

According to the results of the research, Vietnam Airlines is the leader in terms of Net Profit Margin, and its basic strengths are available seat-km and liquidity. In terms of on-time departures, Norwegian Airlines is the leader. Vietnam Airlines also acts as a role model for overall customer satisfaction, having high strength in all the customer satisfaction-related inputs. Finally, Thai Airways is at the top and serves as a role model in terms of passengers carried. Thai Airways' basic strengths are its employees and its fleet. When the relative priority of the four outputs are calculated based on the pairwise comparison matrices of 7 experts from different departments of the airline companies, it is found that financial performance (net profit margin) has the highest priority followed by operational performance (On-time departure) and Marketing Performance (overall customer satisfaction). This makes Vietnam Airlines the top airline company, followed by Norwegian Airlines.

The proposed methodology is used to further discriminate among the efficient airline companies To the best of our knowledge, this is the first study to elaborate upon the network-based approach to airline company performance evaluation, and being able to identify each efficient DMU's strengths and weaknesses has significant managerial implications. An airline company will be able to know which areas to improve and from which organization to learn for this particular area.

Policy makers in the field can use the results of the proposed methodology to gain insight into differentiating operational features and to take strategic actions, such as resource planning.

As a further suggestion, using the regional classification of the International Air Transport Association (IATA), the proposed methodology can be applied to analyze whether there are regional differences in terms of efficiency. The proposed methodology can also be applied to the worldwide known airports to see which airports are working efficiently, and whether there are differences with respect to the regions.

On the other hand, since the evaluated airline companies are from all around the world, the difference of government's police may directly affect their efficiency. For example, fiscal policies such as taxes on airline tickets will increase consumer prices, and affect demands in its turn. Thus, as another further suggestion it may be rational to analyze the impact of such policy indicators on airline's efficiency.

Additionally, Hyperlink-Induced Topic Search (HITS) (Kleinberg, 2007), also known as the hub and authorities centrality measure, can be used as the weight of the superefficiency values. This measure is more suitable for networks having two types of nodes, as is the case in the DEA models where there are only efficient and inefficient DMUs. The hubs and authorities algorithm distinguishes between units that are authorities (efficient units in the DEA model) and units that contribute to the quality of authorities (inefficient units), ranking both classes of nodes. Therefore, it can rank the efficient and inefficient nodes separately.

Finally, instead of using eigenvector centrality as the weight of the superefficiency scores, in addition to eigenvector centrality, different social network analysis indexes can be computed for the airlines and the values of superefficiency scores and the social network indexes can be integrated by a multiattribute decision making technique such as TOPSIS in order to get a richer information about the efficiency of the airlines (Lozano and Calzada-Infante, 2019)

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