Journal of Air Transport Management 44-45 (2015) 34–41

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Evaluating energy efficiency for airlines: An application of VFB-DEA

Qiang Cui [a, *], Ye Li [b]

[a] Transportation Management College, Dalian Maritime University, No.1 Linghai Road, Dalian City, 116026, China
[b] Faculty of Management and Economics, Dalian University of Technology, No.2 Linggong Road, Dalian City, 116024, China

ARTICLE INFO

Article history:
Received 28 March 2014
Received in revised form
11 February 2015
Accepted 18 February 2015
Available online

Keywords:
Energy efficiency
Airlines
VFB-DEA

ABSTRACT

In this paper, the energy efficiency of airlines has been studied with number of employees, capital stock and tons of aviation kerosene as the inputs and Revenue Ton Kilometers, Revenue Passenger Kilometers, total business income and CO_2 emissions decrease index as the outputs. A new model, Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA), is proposed to calculate the energy efficiencies of 11 airlines from 2008 to 2012. Spearman correlation coefficient is applied to validate the applicability of the new model. The results indicate that capital efficiency is an important factor in driving energy efficiency, and the American financial crisis had a significant influence on the change in energy efficiency during this period.

1. Introduction

In recent years, with the rapid development of the world economy and the improvement of the household consumption level, the gap between the demand and supply of energy has widened. According to the statistical data of the International Air Transport Association (2013), in 2012, the total energy cost of all of the airlines in the world was more than 160 billion dollars, and the carbon dioxide emission volume was more than 0.676 billion tons. Airline industry is one of the few sectors where energy consumption has increased at a rate of more than 6% over the past 10years. However, energy production has lagged behind, increasing at less than 6% over the same period. The gap between the energy supply and demand is becoming more and more pronounced. Meanwhile, according to the Commercial Aircraft Corporation of China (COMAC, 2014) forecast for the coming 20 years, the Revenue Passenger Kilometers (RPK) of the total aviation industry will increase by 4.8% a year, and the total passenger transport demand will be 2.6 times the current level. This huge demand for air transport will stimulate a much higher level of energy consumption. Furthermore, in 2011, the aviation industry produced approximately 676 million tons of CO_2, which is approximately 2% of the total global CO_2 emissions. Thus, the energy utilization problem of the airline industry has drawn great public attention. Energy efficiency is defined to reflect whether energy has been used efficiently (Clinch et al., 2001; Blomberg et al., 2012). For the past few years, energy efficiency has been a popular research topic, and many papers have focused on the evaluation of energy efficiency.

The energy efficiencies of different countries, regions and industries have been evaluated (Herring, 2006; Zhou et al., 2008; Worrell et al., 2009; Kaufman and Palmer, 2012; Wang et al., 2012; Hasanbeigi et al., 2013; Cui et al., 2014; Cui and Li, 2015), and the main research method is Data Envelopment Analysis. In Clinch et al. (2001), the energy efficiency of Ireland's dwelling industry was evaluated, and the national savings in energy costs, CO_2 and other environmental emissions were also assessed. Ramanathan (2005) used the Data Envelopment Analysis model to analyze the energy consumption and carbon dioxide emissions from 17 countries of the Middle East and North Africa. Önüt and Soner (2006) evaluated the energy efficiency of 32 five-star hotels in the Antalya Region. In Azadeh et al. (2007), an integrated approach based on data envelopment analysis (DEA), principal component analysis (PCA) and numerical taxonomy (NT) was proposed to assess the total energy efficiency of manufacturing sectors in some OECD (Organization for Economic Cooperation and Development) countries. In Zhou and Ang (2008), the Data Envelopment Analysis model was applied to measure the energy efficiencies of 21 OECD countries. In Mukherjee (2008a), Data Envelopment Analysis was used to measure energy efficiency in the Indian manufacturing sector. Mukherjee (2008b) measured the energy use efficiency of the U.S. manufacturing sector from 1970 to 2001 using the Data Envelopment Analysis model. Song et al. (2013) utilized a Super-SBM model to measure and calculate the

* Corresponding author.
E-mail address: cuiqiang1011@163.com (Q. Cui).

http://dx.doi.org/10.1016/j.jairtraman.2015.02.008
0969-6997/

energy efficiency of the BRIC countries. Wang et al. (2013) analyzed the total-factor energy and environmental efficiency of 29 administrative regions of China during the period from 2000 to 2008 through an improved Data Envelopment Analysis model. In Cui et al. (2014), the inputs and outputs of energy efficiency were calculated by the Economics Value Added (EVA) method. Data Envelopment Analysis (DEA) and the Malmquist index were applied to calculate the energy efficiencies of nine countries during the period from 2008 to 2012. Cui and Li (2014) proposed a three-stage virtual frontier DEA model to evaluate the energy efficiency of transportation sectors in 30 Chinese provincial administrative regions during 2003–2012.

Babikian et al. (2002) analyzed the fuel efficiency of different aircraft types, and the results showed fuel efficiency differences could be explained largely by differences in aircraft operations. Morrell (2009) analyzed the potential for greater fuel efficiency through using larger aircraft and different operational patterns. Miyoshi and Merkert (2010) evaluated carbon and fuel efficiency of 14 European airlines during the period from 1986 to 2007 to understand the relationship between fuel efficiency and fuel price, distance flown and load factors. Zou et al. (2014) employed ratio-based, deterministic and stochastic frontier approaches to investigate fuel efficiency of fifteen large jet operators in the U.S. The results showed that potential cost savings of mainline airlines could reach approximately one billion dollars in 2010.

However, the evaluation of fuel efficiency or energy efficiency for airlines in the above papers has not considered the undesirable output. In the existing energy efficiency papers, the main undesirable outputs are CO_2 emissions in Wei et al. (2007), CO_2 emissions in Zhou and Ang (2008), CO_2 emissions in Mandal (2010) and CO_2 emissions in Tao et al. (2012). This paper chooses CO_2 emissions as the undesirable output. Although airlines contribute only 2% of the global CO_2 emissions, the restriction imposed by the European Union on airline carbon emissions has caught the attention of many airlines.

In most papers, energy efficiency is defined to reflect the relationship between the outputs and the inputs. Based on the general definition of energy efficiency in Patterson (1996), energy efficiency refers to using less energy to produce the same amount of services or useful outputs. And in this paper, energy efficiency of an airline has considered CO_2 emissions based on the basic definition.

2. Methods

2.1. The selection of inputs and outputs

First, this paper summarizes the existing energy efficiency papers to lay a theoretical foundation for building a reasonable index system of airlines' energy efficiency. The inputs and outputs in selected studies are shown in Table 1.

In this paper, based on a review of the literature in Table 1 and the reality of the airline industry, the inputs and outputs of airlines' energy efficiency are selected. Three measurable variables are selected as inputs: labor (number of employees), capital (capital stock) and energy (tons of aviation kerosene). Because more than 95% of the energy consumption is aviation kerosene, this paper chooses it as the index of energy input. Four measurable variables are chosen as outputs: Revenue Ton Kilometers (RTK), Revenue Passenger Kilometers (RPK), total business income and CO_2 emissions decrease index.

Considering the impact of undesirable output on energy efficiency, this paper employs CO_2 emission decrease index as an indicator of airline CO_2 emission. The index is calculated as follows: If the CO_2 emission in year t is C_t and that in year $t-1$ is C_{t-1}, then the CO_2 emission decrease index is C_{t-1}/C_t. This index has two advantages. 1. It can eliminate the linear relationship between energy consumption and CO_2 emission. 2. The index transforms an undesirable output (CO_2 emission) into a desirable output. The larger the index, lower is the CO_2 emission. Furthermore, the index is a positive number, which can avoid the influence of 0 or a negative number on the final results. However, this paper has not considered the difference between jet and turboprop in CO_2 emission. Compared to jet aircrafts, turboprop aircrafts have lower energy consumption and slower speed, this difference may have some influence on the energy efficiency of airlines. This should be improved in the latter research.

2.2. Traditional Data Envelopment Analysis (DEA)

Data Envelopment Analysis (Charnes et al., 1978; Zhou et al., 2008) is a data planning method to evaluate the relative efficiency of decision-making units (DMUs) with multi-inputs and multi-outputs.

Table 1
The inputs and outputs in selected energy efficiency papers.

Papers	Objects	Inputs	Outputs
Boyd and Pang (2000).	Two segments of the glass industry	Electric, Fuel	Add value
Clinch et al. (2001)	Ireland's dwelling stock	Labor input, Cost input, Energy input	Energy benefit, Environmental benefits
Ramanathan (2005)	17 countries	CO_2 emissions per capita, Fossil fuel energy consumption	Gross domestic product per capita, Non-fossil fuel energy consumption
Önüt and Soner (2006)	32 five-star hotels	Number of employees, Annual electricity consumption, Annual water consumption, Annual liquefied petroleum gas consumption	Occupancy rate, Annual total revenue, Total number of guests
Azadeh et al. (2007)	OECD countries	Final consumption of electricity, Thermal aggregation of all fossil fuels final consumptions	Gross output, Value added from both categories
Hu and Kao (2007).	17 APEC economies	Labor input, Capital input, Energy input	Gross Domestic Product
Wei et al. (2007)	China's iron and steel sector	Industrial capital stock, Industrial labor force, Industrial energy consumption	Industrial value added, Industrial CO_2 emissions
Mukherjee (2008a)	Indian manufacturing sector	Labor, Capital, Energy, Materials.	Gross value of manufacturing production
Mukherjee (2008b)	U.S. manufacturing sector	Capital, Labor, Energy, Materials, Services	Gross output
Zhou and Ang (2008)	21 OECD countries	Capital stock, Labor force	Gross Domestic Product, CO_2 emissions
Blomberg et al. (2012)	Swedish pulp and paper industry	Labor, Electricity, Oil	Pulp or paper
Cui et al. (2014)	Nine countries	Number of employees in energy industry, Energy consumption amount, Energy services amount	CO_2 emissions per capita, Industrial profit amount
Cui and Li (2014)	30 provinces of China	Labor input, Capital input, Energy input	Passenger turnover volume, Freight turnover volume

Suppose the data set is (Y, X);Y denotes the $n \times s$ matrix of the outputs and X denotes $n \times m$ matrix of the inputs, $Y = \begin{bmatrix} y_1' \\ \vdots \\ y_n' \end{bmatrix}$, $X = \begin{bmatrix} x_1' \\ \vdots \\ x_n' \end{bmatrix}$. n, s, m stand for the number of decision-making units, the outputs and the inputs, respectively.

The DEA model attempts to measure the ratio of outputs to inputs, such as $u'y_i/_{v'x_i}$, where u, v are the weight vectors of outputs and inputs. For each DMU, the following linear programming problem is formulated:

$$\max \ u'y_i$$

$$s.t. \quad v'x_i = 1$$

$$u'y_j - v'x_j \leq 0, \quad j = 1, 2, \cdots, n$$

$$u \geq 0, \quad v \geq 0$$

Any of the DMUs may or may not be on the frontier when the ratio is measured (Barros and Peypoch, 2009). The distance from the actual allocation of a particular DMU to the frontier is believed to represent the inefficiency of the DMU, which may be caused by various factors, specific to the DMU. If the efficiency of DMU i is 1, DMU i is a technically efficient DMU; if its efficiency less than 1, it is technically inefficient. The above problem assumes constant returns to scale (CRS).

Traditional DEA model has two limitations. 1. Traditional DEA model is based on self-appraisal, and its performance is decided by itself in the process of maximizing its efficiency and minimizing the efficiency of other decision-making units. However, the application field of the traditional DEA model is confined by this self-appraisal. When a large part of DMU's efficiency is from cooperation, the evaluation results of the traditional DEA model are not very accurate (Yang et al., 2011). 2. In the traditional DEA model, each decision-making unit compares its production ability with the production ability of an optimal real frontier (Zhu, 2001; Xue and Harker, 2002). When its result is 1, the DMU is technically efficient; otherwise, the DMU is technically inefficient. However, it cannot distinguish the differences between efficient DMUs.

2.3. The improvement of the first limitation

Aiming at the first limitation, some derived models of Data Envelopment Analysis are put forward; one well-established model is the Benevolent DEA Cross Efficiency model (Doyle and Green, 1994; Yang et al., 2011). In this model, every decision-making unit is considered as a cooperator. When the decision-making unit maximizes its efficiency, it also maximizes other DMUs' efficiencies. It is possible to evaluate the DMUs with cooperation relationship.

The detailed Benevolent Data Envelopment Analysis Cross Efficiency model (Benevolent DEA) will be introduced as follows:

In the CRS model, the efficiency of DMU k can be obtained by the following programming:

$$\gamma = \max \ u'y_k$$

$$s.t. \quad v'x_k = 1$$

$$u'y_j - v'x_j \leq 0, \quad j = 1, 2, \cdots, n$$

$$u \geq 0, \quad v \geq 0$$

For DMU k, the optimal solution is $(\gamma_k^*, u_k^*, v_k^*)$. The optimal solutions of other DMUs can be labeled as $(\gamma_j^*, u_j^*, v_j^*)(j = 1, 2, \cdots n)$, so the cross efficiency of DMU k is

$$E_k = \frac{1}{n} \frac{\sum_{j=1}^{n} u_j' y_k}{\sum_{j=1}^{n} v_j' y_k}$$

According to Doyle and Green (1994), the benevolent cross efficiency of DMU k to DMU l is gotten through following programming:

$$\gamma_{kl} = \max \ u'y_k$$

$$s.t. \quad v'x_k = 1$$

$$u'y_j - v'x_j \leq 0, \quad j = 1, 2, \cdots, n$$

$$u'y_l - \gamma_l^* v'x_l = 0$$

$$u \geq 0, \quad v \geq 0$$

The average benevolent cross efficiency of decision-making unit k is:

$$E_k = \frac{1}{n} \sum_{l=1}^{n} \gamma_{kl}$$

However, the Benevolent DEA model cannot improve the second limitation of DEA model. In its evaluation results, there may still be many efficient DMUs, but the model cannot distinguish the larger ones from the smaller ones.

2.4. The improvement of the second limitation

According to Charnes et al. (1991), the DMUs can be partitioned into two groups: frontier DMUs and non-frontier DMUs. Moreover, the frontier DMUs are of three types: the extremely efficient DMUs, efficient DMUs but not at extreme point and weakly efficient DMUs or frontier point but with non-zero slacks. The Super Data Envelopment Analysis method is proposed to identify the type. The principle of the Super Data Envelopment Analysis model is to exclude the evaluated DMU from the reference DMUs (Andersen and Petersen, 1993; Zhu, 2001; Xue and Harker, 2002; Chen, 2005; Chiu et al., 2011). Its model is:

$$\max \ u'y_i$$

$$s.t. \quad v'x_i = 1$$

$$u'y_j - v'x_j \leq 0, \quad j = 1, 2, \cdots, n, \ j \neq i$$

$$u \geq 0, \quad v \geq 0$$

In general, the results of the Super Data Envelopment Analysis model do not contain the same efficiency. However, it has limitations too. The model is shown in Fig. 1:

As shown in Fig. 1, in the traditional DEA, DMUs A, B, C and D are in the efficient frontier, whereas DMU E is inefficient. In the Super DEA model, when the efficiency of DMU B is calculated, it is excluded from the reference set and the reference set changes from ABCD to ACD. The efficiency of DMU B is $OB_1/_{OB} > 1$. Furthermore, for the DMU E, which is inefficient in the traditional DEA, the frontier remains ABCD, and its efficiency remains unchanged as $OE_1/_{OE} < 1$.

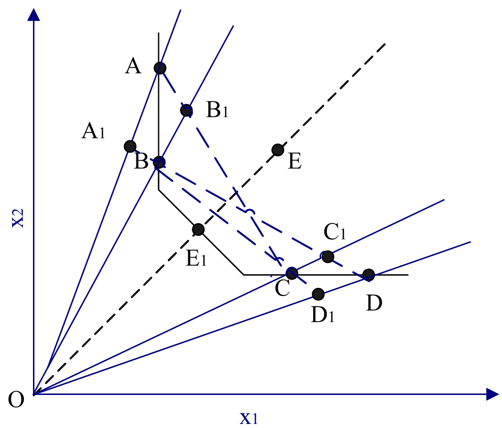

Fig. 1. The Super DEA model.

However, in the Super DEA model, the reference set varies when a different DMU is evaluated, which may lead to unreasonable results. In Fig. 1, the efficiencies of DMUs A, B, C and D in Super DEA are $OA_1/_{OA} < 1$, $OB_1/_{OB} > 1$, $OC_1/_{OC} > 1$ and $OD_1/_{OD} < 1$. Compared with the traditional DEA model, the efficiencies of DMUs A and D become lower, while that of DMUs B and C become larger. These differences are caused by the different reference sets, which may make the results unreasonable.

To overcome the disadvantage, Virtual Frontier Data Envelopment Analysis is proposed by Bian and Xu (2013) and derived models can be seen in Cui and Li (2014, 2015).

To better explain the Virtual Frontier Data Envelopment Analysis model, Fig. 2 is introduced. In the traditional DEA model, where A, B, C, D and E are the DMUs, A, B, C, D are DEA efficient and E is DEA inefficient. The efficiencies of A, B, C and D are the same as 1, so the traditional DEA model cannot differentiate them.

Virtual Frontier Data Envelopment Analysis in this paper constructs a virtual frontier FGHI as the optimal reference frontier of A, B, C, D and E and then A, B, C, D, E are DEA inefficient. Their efficiencies can be differentiated.

If ζ denotes the evaluating DMU set and ψ is the reference DMU set (the virtual frontier), the virtual frontier Data Envelopment Analysis model is

$$\max \ u'y_i$$

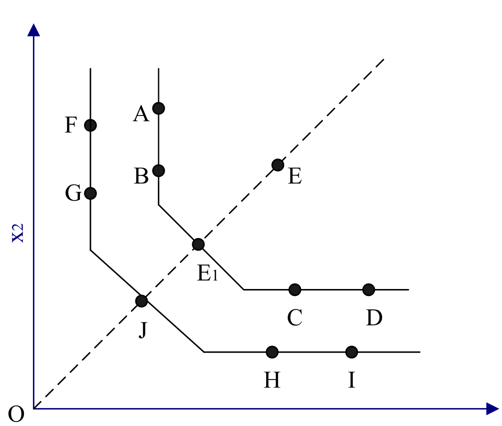

Fig. 2. The principle of virtual frontier DEA.

$$s.t. \quad v'x_i = 1$$

$$u'y_J - v'x_J \le 0, \quad J = 1,\ 2, \cdots, n, \ J \in \psi$$

$$u \ge 0, \quad v \ge 0$$

In this model, the reference DMU set and the evaluating DMU set are two different sets; this offers the possibility of distinguishing between the DEA efficient DMUs in the traditional DEA model. And in the evaluating process, the reference DMU set remains unchanged so that its results may be more reasonable than those from the Super Data Envelopment Analysis model.

Next, this paper will introduce the selection of a reference DMU set. According to the literature (Bian and Xu, 2013; Cui and Li, 2014, 2015), the number of reference DMUs should be equal to evaluating DMUs.

Set $x_{i0} = \min_j \{x_{i,j}\}$ and $y_{r0} = \max_j \{y_{rj}\}$, $j = 1,\ 2, \ldots, n$ represent the DMUs, x_{ij} denotes the i th input of DMU j, y_{rj} denotes the r th output of DMU j. For the DMU J of reference set, its input are set as $x_{iJ} = 0.95\ x_{i0}$ and its output are set as $y_{rJ} = 1.05\ y_{r0}$.

From the selection of the reference DMU set, it can be concluded that the inputs of reference DMU J are less than the real DMU j, and its outputs are larger than the real DMU. Therefore, the efficiency number from the Virtual Frontier DEA model is lower than the number from the traditional DEA model, which can ensure that the efficiency number from the Virtual Frontier DEA model is less than 1 and equal to or larger than 0.

Based on the limitations of the traditional Data Envelopment Analysis model and the introductions in Sections 2.4 and 2.5, this paper will propose a new model, the Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA), in hope of solving the two limitations of the traditional DEA model.

2.5. Virtual Frontier Benevolent DEA cross efficiency model (VFB-DEA)

In the Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA), the VFB-DEA cross efficiency of DMU k to DMU l can be gotten through following programming:

$$\gamma_{kl} = \max \ u'y_k$$

$$s.t. \quad v'x_k = 1$$

$$u'y_J - v'x_J \le 0, \quad J = 1,\ 2, \cdots, n, \ J \in \psi$$

$$u'y_l - \gamma_l^* v'x_l = 0, \ \ l = 1,\ 2, \cdots n$$

$$u \ge 0, \quad v \ge 0$$

ψ is the reference DMU set.

The average VFB-DEA efficiency of decision-making unit k is:

$$E_k = \frac{1}{n} \sum_{l=1}^{n} \gamma_{kl}.$$

The two models solve the two limitations of the traditional DEA model, and the specific performances are: 1. The DMUs in the VFB-DEA model maximize their own efficiencies as well as maximize other DMUs' efficiencies, which can reflect the cooperation relationship of the DMUs. For most DMUs, although the task of maximizing its own efficiency is superior to maximizing other DMUs' efficiency, the embodiment of the cooperation relationship is very important to make the results more convincing in some situations. 2. In the VFB-DEA model, all DMUs are inefficient and their efficiencies are less than 1; therefore, it is possible to distinguish between the efficient DMUs in the traditional DEA. Compared with Super DEA, the reference frontiers in VFB-DEA remain unchanged, which probably makes the evaluation results more reasonable.

3. Results

3.1. The data

An empirical study in this paper will be performed with the data of a five-year period, from 2008 to 2012. Since 2008, the financial crisis in the U.S. has deeply affected the global airline and the energy markets. To minimize the effect of the financial crisis, many airlines anchor their hope on improving overall efficiency, and on account of the increasing energy price, energy efficiency has become an important consideration. It is meaningful to study the energy efficiencies of some of the major airlines during this period.

The empirical data are obtained from 11 airlines: China Eastern Airlines, China Southern Airlines, Air China, Hainan Airlines, Korean Air, Qantas Airways, Air France-KLM, Lufthansa Airlines, Scandinavian Airlines, Delta Air Lines and Alaska Airlines. Out of these 11 airlines, the passenger capacity of five ranked in the top 10 worldwide, in 2012 (Delta Air Lines, Lufthansa Airlines, Air France-KLM, China Eastern Airlines and China Southern Airlines). These 11 airlines come from Asia, America, Europe and Oceania, so they are representative of global airlines to a certain degree. For simplicity, this paper has not considered the impacts of different company types, such as the difference between low-cost carriers and full service carriers. The data on number of employees, capital stock, total business income, Revenue Ton Kilometers and Revenue Passenger Kilometers are collected from the annual reports. The data on tons of aviation kerosene and CO_2 emission volume are taken from the sustainability, environment and corporate social responsibility reports of the 11 companies.

On August 20, 2013, in the 38th executive committee meeting of the International Civil Aviation Organization, the cooperation among airlines on energy use standards and development of sustainable environment was noted, and the future prospect of using alternative energy was analyzed. Furthermore, although the airlines belong to different airline alliances, increasingly higher level of cooperative relationships are being reported in the annual as well as the corporate social responsibility reports, especially in the context of the global financial crisis, high oil price and low effective demand. The exchange of energy technology is found to be more prevalent now than during the period before the global financial crisis. Based on the above information, this paper qualitatively judges that the airlines are cooperating on energy efficiency and the VFB-DEA model can be applied to evaluate the energy efficiencies. To verify this qualitative judgment, a quantitative analysis will be provided in Section 3.3.

Here, each airline is defined as a decision making unit (DMU) and each DMU has three inputs and four outputs. The data of China Eastern Airlines is taken as an example and shown in Appendix A.

3.2. Results of the traditional DEA model

To verify the reasonability of the new model, first, this paper uses the traditional DEA model to calculate the energy efficiencies. The results using DEAP 2.1 software are shown in Table 2.

Table 2
Results of the traditional DEA model.

Airlines	2008	2009	2010	2011	2012
China Eastern Airlines	1.000	1.000	1.000	0.945	1.000
China Southern Airlines	1.000	1.000	1.000	1.000	1.000
Korean Air	1.000	1.000	1.000	1.000	1.000
Qantas Airways	1.000	1.000	1.000	1.000	1.000
Air France-KLM	1.000	1.000	1.000	1.000	1.000
Lufthansa Airlines	0.801	0.730	0.785	1.000	0.864
Scandinavian Airlines	1.000	1.000	1.000	1.000	1.000
Delta Air Lines	1.000	1.000	1.000	1.000	1.000
Alaska Airlines	1.000	1.000	1.000	1.000	1.000
Air China	1.000	0.958	0.832	0.975	0.831
Hainan Airlines	0.806	0.290	0.331	0.366	0.246

As shown in Table 2, the efficiencies of many DMUs are 1, and traditional DEA cannot distinguish them.

Table 3
Results of the Benevolent DEA model.

Airlines	2008	2009	2010	2011	2012
China Eastern Airlines	1.000	1.000	1.000	0.945	1.000
China Southern Airlines	1.000	1.000	1.000	1.000	1.000
Korean Air	1.000	1.000	1.000	1.000	1.000
Qantas Airways	1.000	1.000	1.000	1.000	1.000
Air France-KLM	1.000	1.000	1.000	1.000	1.000
Lufthansa Airlines	0.799	0.730	0.783	0.882	0.863
Scandinavian Airlines	1.000	1.000	1.000	1.000	1.000
Delta Air Lines	1.000	1.000	1.000	1.000	1.000
Alaska Airlines	0.893	1.000	0.952	1.000	1.000
Air China	0.989	0.956	0.832	0.975	0.831
Hainan Airlines	0.097	0.075	0.084	0.101	0.097

3.3. Results of the benevolent DEA model

In this paper, the Benevolent DEA model is conducted through MATLAB programming; its results are shown in Table 3.

As shown in Table 3, all DMUs' efficiencies from the Benevolent DEA model are less than or equal to those from the traditional DEA model. Through analyzing the Benevolent DEA model, we can infer that although each DMU maximizes other DMUs' efficiencies while it maximizes its own, each DMU gives the highest priority to making its own efficiency higher. This self interest drives down the efficiency value of all of the DMUs.

Comparing Table 3 with Table 2, the efficiency change for Hainan Airlines is the largest. In Table 2, Hainan Airlines is an efficient DMU through the period from 2008 to 2012. However, it becomes the least efficient DMU in Table 3. The results show that Hainan Airlines gets the least benefit from the cooperative relationship.

From the results, it can be concluded that although most DMUs' efficiencies from the Benevolent DEA model are less than those from the traditional DEA model, even the Benevolent DEA model cannot distinguish some DMUs. Thus, the second limitation of the traditional DEA cannot be solved by the Benevolent DEA model.

Next, according to the literature (Yang et al., 2011), this paper employs clustering analysis method to verify the judgment on the cooperation relationships in the previous section. Its principle is based on the distance of the cross efficiencies among the DMUs. The distance between DMU i and DMU j is

$$d_{ij} = \sqrt{(\gamma_{i1} - \gamma_{j1})^2 + (\gamma_{i2} - \gamma_{j2})^2 + \cdots + (\gamma_{in} - \gamma_{jn})^2}$$

γ denotes the cross efficiency obtained from Benevolent DEA model.

Then, the 11 DMUs will be labeled as 11 groups, and the two groups whose distance is the least are organized into a new group; the distance between the two groups is

$$d_{IJ} = \frac{1}{N_I N_J} \sum_{i=1}^{N_I} \sum_{j=1}^{N_J} d_{ij}$$

N_I and N_J stand for the number of DMUs in groups I and J.

When distances among the groups are calculated, the two groups with the least distance will be organized into a new group; there will still be nine groups. Following this step, the group number reduces by one, after two groups are integrated into one group. The steps will continue until the group distance is larger than a threshold value.

According to Yang et al. (2011) and the real results of the efficiency scores, in this paper, the threshold value is set as 0.6. The results of clustering analysis show that all of the 11 DMUs fall into one group finally, which verifies the judgment on the cooperation relationships in Section 3.1.

3.4. Results of the virtual frontier DEA model

This paper runs Virtual Frontier DEA model through Matlab programming; the results are shown in Table 4.

From Table 4, it can be concluded that the Virtual Frontier DEA model can distinguish the DMUs, as all DMUs' efficiencies are not the same. Because the reference DMUs have larger outputs and lower levels of inputs, all DMUs' efficiencies are less than those from the traditional DEA model. When the reference DMUs are DEA efficient, all evaluated DMUs' efficiencies are less than those from the traditional DEA model.

In the Virtual Frontier DEA model, all of the airlines are inefficient; so the difference in the efficiencies can be shown, which improves the second limitation of the traditional DEA model.

3.5. Results of the VFB-DEA model

Based on the two previously mentioned limitations, and synthesizing the Benevolent DEA model and the Virtual Frontier DEA model, this paper proposes Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA). The results of VFB-DEA are shown in Table 5.

4. Discussions

4.1. Discussion of the results

As shown in Table 5, the average energy efficiency of Delta Air Lines over the period from 2008 to 2012 is the highest. The main reason lies in its high capital efficiency. Its average RTK of unit capital stock ranks first and is approximately 86.68 ton-kilometers per hundred dollars, whereas that of the least efficient Hainan Airlines is approximately 1.90 ton-kilometers per hundred dollars. Delta's average RPK of unit capital stock ranks first and is approximately 1263.73 person-kilometers per hundred dollars, while that of the least efficient Hainan Airlines, is approximately 9.24 person-kilometers per hundred dollars. Delta's average business income of unit capital stock ranks first and is approximately 1.45, while that of the least efficient Hainan Airlines, is approximately 0.30. Delta's average CO_2 emission decrease index of unit capital stock ranks second after Scandinavian Airlines (0.0092) and is approximately 0.0076 per 10^8 dollars, while that of the least efficient Hainan Airlines, is approximately 0.0030 per 10^8 dollars. Thus, high capital efficiency has a significant impact on airlines' energy efficiency.

The average energy efficiency of Chinese airlines (China Eastern Airlines, China Southern Airlines, Air China and Hainan Airlines) is 0.669 and is less than the average level of the 11 airlines (0.730). China Eastern Airlines ranks first in the four Chinese airlines. The energy efficiency of China Eastern Airlines has been improved through optimizing fleets, optimizing air route and applying new technology. In 2012, China Eastern Airlines sold five planes A340-300 with high fuel consumption and upgraded 16 engines. With each engine saving 410.5 tons of standard coal per year, these 16 engines could save 6586 tons of standard coal every year. The application of Performance Based Navigation (PBN) can help China Eastern Airlines save 34,000 tons of aviation kerosene in each year.

The situation during the period from 2008 to 2009 should be noted as all the airlines' energy efficiencies decreased in that time. The financial crisis in the U.S.A. has greatly affected the energy efficiency of the airlines. During this period, the Revenue Ton Kilometers, the Revenue Passenger Kilometers and the business income of almost all of the airlines declined sharply, whereas there was a minor change in the labor and the capital inputs; this led to the reduction of the energy efficiency.

4.2. Verification of the new model

To verify the rationality of VFB-DEA, this paper compares it with the traditional DEA model, the Virtual Frontier DEA model and the Benevolent DEA model. The main measurement index is the Spearman correlation coefficient (Bonneterre et al., 1990; Lesurtel et al., 2003). It reflects the relevance between the energy efficiency and the output of each input. If the Spearman correlation coefficient is large, there is high relevance between the two indices. The average energy efficiency from 2008 to 2012 of each DMU is defined as the comprehensive energy efficiency. For each output, its output capacity of unit input can be defined as the average value of the quotients between its value and each input. For example, for Revenue Ton Kilometers, its output capacity of unit input is the average value of Revenue Ton Kilometers/number of employees, Revenue Ton Kilometers/capital stock and Revenue Ton Kilometers/

Table 4
Results of the Virtual Frontier DEA model.

Airlines	2008	2009	2010	2011	2012
China Eastern Airlines	0.783	0.599	0.865	0.863	0.930
China Southern Airlines	0.658	0.511	0.705	0.718	0.793
Korean Air	0.691	0.558	0.846	0.842	0.871
Qantas Airways	0.737	0.575	0.882	0.881	0.861
Air France-KLM	0.892	0.623	0.936	0.952	0.841
Lufthansa Airlines	0.749	0.608	0.868	0.888	0.886
Scandinavian Airlines	0.940	0.941	0.922	0.952	0.909
Delta Air Lines	0.985	0.912	0.945	0.953	0.986
Alaska Airlines	0.661	0.578	0.876	0.860	0.846
Air China	0.748	0.577	0.753	0.727	0.890
Hainan Airlines	0.726	0.554	0.640	0.637	0.837

Table 5
Results of the VFB-DEA model.

Airlines	2008	2009	2010	2011	2012	Average	Order
China Eastern Airlines	0.660	0.569	0.803	0.802	0.894	0.746	4
China Southern Airlines	0.613	0.514	0.663	0.668	0.768	0.645	10
Korean Air	0.594	0.516	0.792	0.789	0.803	0.699	7
Qantas Airways	0.707	0.510	0.812	0.805	0.826	0.732	5
Air France-KLM	0.779	0.586	0.907	0.906	0.816	0.799	3
Lufthansa Airlines	0.640	0.563	0.785	0.788	0.803	0.716	6
Scandinavian Airlines	0.856	0.854	0.852	0.874	0.835	0.854	2
Delta Air Lines	0.913	0.841	0.893	0.891	0.884	0.884	1
Alaska Airlines	0.580	0.486	0.754	0.753	0.763	0.667	9
Air China	0.694	0.485	0.685	0.692	0.785	0.668	8
Hainan Airlines	0.651	0.536	0.561	0.563	0.773	0.617	11

Table 6
Comparison of the four models.

Output capacity	VFB-DEA	Traditional DEA model	Benevolent DEA model	Virtual frontier DEA model
RTK	0.722***[b] (0.001[a])	0.484***[b] (0.001[a])	0.677***[b] (0.000[a])	0.632***[b] (0.000[a])
RPK	0.676***[b] (0.001[a])	0.531***[b] (0.000[a])	0.543***[b] (0.000[a])	0.565***[b] (0.000[a])
Total business income	0.855***[b] (0.000[a])	0.635***[b] (0.000[a])	0.744***[b] (0.001[a])	0.663***[b] (0.000[a])
CO_2 decrease index	0.455***[b] (0.000[a])	0.411***[b] (0.000[a])	0.423***[b] (0.000[a])	0.377***[b] (0.001[a])

[a] The number in bracket denotes the p value.
[b] *** stand for the variable is significant on 1%.

aviation kerosene. Then, the comprehensive output capacity of unit input is the average value from 2008 to 2012. Thus, for each DMU, there are four comprehensive output capacities of unit input. Spearman correlation coefficient can reflect the consistency between the change trend of energy efficiency and the change trend of the four comprehensive output capacities of unit input. If one model can pass the significance test and its coefficients are larger than those from the other three models, the relevance between the output capacity and energy efficiency in this model are higher than those from other models. Thus, this model is more suitable to evaluate the energy efficiencies of airlines. The comparison results are shown in Table 6.

The results in Table 6 show that the relevance between energy efficiency and the output capacity in the VFB-DEA model is the highest, so the model is suitable to evaluate the energy efficiencies of the airlines.

5. Conclusions

The topic of airlines' energy efficiency is studied in this paper. Number of employees, capital stock and tons of aviation kerosene are chosen as the inputs. Revenue Ton Kilometers, Revenue Passenger Kilometers, total business income and CO_2 emission volume are selected as the outputs. A new model, the Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA), is proposed and applied to evaluate the energy efficiencies of 11 airlines from 2008 to 2012. The results verify the rationality of the new model.

On the whole, the contribution of this paper to the literature is embodied in two aspects. First, based on the existing paper on airlines' energy efficiency, this paper considers the undesirable output. The idea in this paper enriches the theory and method of energy research and supplies a new view on evaluating the development of the airlines. Second, a new model, the Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA) is proposed. It can resolve two limitations of the traditional DEA model: 1. the limitation of self-appraisal, and 2. the limitation in distinguishing DEA efficient DMUs. The results verify the rationality of the new model.

Focusing on evaluating energy efficiency for airlines, this paper has not analyzed the roles that some important factors play in determining the relative efficiency performance of different airlines. The factors can be incorporated into a two-stage bootstrapped DEA (Merkert et al., 2010; Merkert and Hensher, 2011) to seek their impacts on energy efficiency.

Acknowledgments

This research is funded by National Nature Science Foundation of China: (NO. 71403034; NO. 71273037; NO. 71320107006).

Appendix A. The inputs and outputs (take China Eastern Airlines as an example)

Years	Number of employees	Capital stock (10^8 dollars)	Aviation kerosene (10^4 tons)	Revenue ton kilometers (10^6 ton-kilometers)	Revenue Passenger kilometers (10^6 person-kilometers)	Total business income (10^8dollars)	CO_2 emission decrease index
2008	44153	119.00	240.98	7218.99	53785.27	68.04	1.03
2009	45938	117.10	260	7909.00	60942.00	64.77	1.01
2010	37600	163.92	292	4308.00	93153.00	121.88	1.00
2011	38067	182.46	387.8	4421.00	100895.00	136.54	0.87
2012	41235	196.69	414.3	14406.48	109112.68	139.14	1.03

References

Andersen, P., Petersen, N.C., 1993. A procedure for ranking efficient units in data envelopment analysis. Manag. Sci. 39, 1261–1294.
Azadeh, A., Amalnick, M.S., Ghaderi, S.F., Asadzadeh, S.M., 2007. An integrated DEA PCA numerical taxonomy approach for energy efficiency assessment and consumption optimization in energy intensive manufacturing sectors. Energy Policy 35, 3792–3806.
Babikian, R., Lukachko, S.P., Waitz, I.A., 2002. The historical fuel efficiency characteristics of regional aircraft from technological, operational, and cost perspectives. J. Air Transp. Manag. 8 (6), 389–400.
Barros, C.P., Peypoch, N., 2009. An evaluation of European airlines' operational performance. Int. J. Prod. Econ. 122 (2), 525–533.
Bian, Y.W., Xu, H., 2013. DEA ranking method based upon virtual envelopment frontier and TOPSIS. Syst. Eng. Theory Pract. 33 (2), 482–488 (in Chinese).
Blomberg, J., Henriksson, E., Lundmark, R., 2012. Energy efficiency and policy in Swedish pulp and paper mills: a data envelopment analysis approach. Energy Policy 42, 569–579.
Bonneterre, J., Peyrat, J.P., Beuscart, R., Demaille, A., 1990. Prognostic significance of insulin-like growth factor 1 receptors in human breast cancer. Cancer Res. 50 (21), 6931–6935.
Boyd, G.A., Pang, J.X., 2000. Estimating the linkage between energy efficiency and productivity. Energy Policy 28, 289–296.
Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444.
Charnes, A., Cooper, W.W., Thrall, R.M., 1991. A structure for classifying and characterizing efficiencies and inefficiencies in DEA. J. Prod. Anal. 2, 197–237.
Chen, Y., 2005. Measuring super-efficiency in DEA in the presence of infeasibility. Eur. J. Oper. Res. 161, 545–551.
Chiu, Y.H., Chen, Y.C., Bai, X.J., 2011. Efficiency and risk in Taiwan banking: SBM super-DEA estimation. Appl. Econ. 43 (5), 587–602.
Clinch, J.P., Healy, J.D., King, C., 2001. Modelling improvements in domestic energy efficiency. Environ. Model. Softw. 16 (1), 87–106.
COMAC, 2014. http://www.comac.cc/xwzx/gsxw/201411/11/t20141111_2075388.shtml.
Cui, Q., Li, Y., 2014. The evaluation of transportation energy efficiency: an application of three-stage virtual frontier DEA. Transp. Res. D 29, 1–11.

Cui, Q., Li, Y., 2015. An empirical study on the influencing factors of transportation carbon efficiency: evidences from fifteen countries. Appl. Energy 141, 209–217.

Cui, Q., Kuang, H.B., Wu, C.Y., Li, Y., 2014. The changing trend and influencing factors of energy efficiency: the case of nine countries. Energy 64, 1026–1034.

Doyle, J., Green, R., 1994. Efficiency and cross efficiency in DEA: derivations, meanings and the uses. J. Oper. Res. Soc. 45, 567–578.

Hasanbeigi, A., Morrow, W., Sathaye, J., Masanet, E., Xu, T., 2013. A bottom-up model to estimate the energy efficiency improvement and CO_2 emission reduction potentials in the Chinese iron and steel industry. Energy 50, 315–325.

Herring, H., 2006. Energy efficiency—a critical view. Energy 31, 10–20.

Hu, J.L., Kao, C.H., 2007. Efficient energy-saving targets for APEC economies. Energy Policy 35, 373–382.

International Air Transport Association, 2013. http://www.iata.org/Pages/default.aspx.

Kaufman, N., Palmer, K.L., 2012. Energy efficiency program evaluations: opportunities for learning and inputs to incentive mechanisms. Energy Effic. 5, 243–268.

Lesurtel, M., Cherqui, D., Laurent, A., Tayar, C., Fagniez, P.L., 2003. Laparoscopic versus open left lateral hepatic lobectomy: a case-control study. J. Am. Coll. Surg. 196 (2), 236–242.

Mandal, S.K., 2010. Do undesirable output and environmental regulation matter in energy efficiency analysis? Evidence from Indian cement industry. Energy Policy 38 (10), 6076–6083.

Merkert, R., Smith, A.S.J., Nash, C.A., 2010. Benchmarking of train operating firms – a transaction cost efficiency analysis. J. Transp. Plan. Technol. 33, 35–53.

Merkert, R., Hensher, D.A., 2011. The impact of strategic management and fleet planning on airline efficiency—A random effects Tobit model based on DEA efficiency scores. Transp. Res. A 45 (7), 686–695.

Miyoshi, C., Merkert, R., 2010. Changes in carbon efficiency, unit cost of firms over time and the impacts of the fuel price—an empirical analysis of major European airlines. In: Proceedings of the 14th Air Transport Research Society (ATRS) World Conference, Porto, Portugal.

Morrell, P., 2009. The potential for European aviation CO_2 emissions reduction through the use of larger jet aircraft. J. Air Transp. Manag. 15, 151–157.

Mukherjee, K., 2008a. Energy use efficiency in the Indian manufacturing sector: an interstate analysis. Energy Policy 36, 662–672.

Mukherjee, K., 2008b. Energy use efficiency in US manufacturing: a nonparametric analysis. Energy Econ. 30, 76–97.

Önüt, S., Soner, S., 2006. Energy efficiency assessment for the Antalya region hotels in Turkey. Energy Build. 38, 964–971.

Patterson, M.G., 1996. What is energy efficiency? Concepts, indicators and methodological issues. Energy Policy 24 (5), 377–390.

Ramanathan, R., 2005. An analysis of energy consumption and carbon dioxide emissions in countries of the Middle East and North Africa. Energy 30, 2831–2842.

Song, M.L., Zhang, L.L., Liu, W., Fisher, R., 2013. Bootstrap-DEA analysis of BRICS' energy efficiency based on small sample data. Appl. Energy 112, 1049–1055.

Tao, F., Li, L., Xia, X.H., 2012. Industry efficiency and total factor productivity growth under resources and environmental constraint in China. Sci. World J. http://dx.doi.org/10.1100/2012/310407.

Wang, K., Yu, S., Zhang, W., 2013. China's regional energy and environmental efficiency: a DEA window analysis based dynamic evaluation. Math. Comput. Model. 58 (5), 1117–1127.

Wang, Z.H., Yang, Z.M., Zhang, Y.X., Yin, J.H., 2012. Energy technology patents-CO_2 emissions nexus: an empirical analysis from China. Energy Policy 42, 248–260.

Wei, Y.M., Liao, H., Fan, Y., 2007. An empirical analysis of energy efficiency in China's iron and steel sector. Energy 32, 2262–2270.

Worrell, E., Bernstein, L., Roy, J., Price, L., Harnisch, J., 2009. Industrial energy efficiency and climate change mitigation. Energy Effic. 2, 109–123.

Xue, M., Harker, P.T., 2002. Ranking DMUs with infeasible super-efficiency DEA methods. Manag. Sci. 48 (5), 705–710.

Yang, F., Xia, Q., Liang, L., 2011. DEA cross efficiency evaluation method for competitive and cooperative decision making units. Syst. Eng. Theory Pract. 31 (1), 92–98 (in Chinese).

Zhou, P., Ang, B.W., 2008. Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy 38, 2911–2916.

Zhou, P., Ang, B.W., Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. Eur. J. Oper. Res. 189 (1), 1–18.

Zhu, J., 2001. Super-efficiency and DEA sensitivity analysis. Eur. J. Oper. Res. 129, 443–455.

Zou, B., Elke, M., Hansen, M., Kafle, N., 2014. Evaluating air carrier fuel efficiency in the US airline industry. Transp. Res. A 59, 306–330.