AN APPLICATION OF DEA TO MEASURE THE EFFICIENCY OF LEADING CARGO AIRLINES

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Abstract: The air cargo industry is very important in the global economy, due to the fact that it is recognized as the main mode of transport for perishable goods, luxury goods, and other high value products. In order to survive in highly competitive market, cargo airlines must identify the needs of their customers and provide the appropriate services. The common measure that implies how much a firm can meet its predetermined goals is the efficiency. This paper provides the efficiency analysis of the 18 world leading cargo airlines in 2017. A Date Envelopment Analysis (DEA) models with three inputs and two outputs are created to assess and optimize the cargo airline productivity. In these models the efficiency indicators such as number of employee, number of aircraft and offered capacity are defined as inputs, while realized traffic and revenue are defined as outputs. The basic model was used to evaluate the efficiency of the selected cargo airlines and it provides satisfactory results. However, in order to improve these results and to evaluate the operation indicators which affect cargo airline efficiency and which are not in the same order of magnitude, the weighted DEA is proposed. The weights are derived by using Analytic Hierarchy Process (AHP). The results of the models include a benchmark and cargo airlines ranking, as well as the directions for improving the efficiency of inefficient airlines. Moreover, it is shown that the weighted DEA provides more logical results, since the relationship between the indicators is defined in accordance with their real significance. It should be noted that this is the first research where integrated AHP and DEA are used for assessing the efficiency in cargo airline industry. The high flexibility of the proposed models enables its application on different markets as well as on all types of airlines.

Keywords: Cargo Airline Efficiency, DEA, AHP.

1. INTRODUCTION

World trade is increasingly more dependent on air cargo services, despite being a costlier mode of transportation. Air cargo is growing in popularity as the choice when it comes to shipping time sensitive goods, belongings, and documents from one place to another. Moreover, the demand growth of air freight is being impacted by the rise of e-commerce that put pressures on sales channels for faster delivery and optimum supply chain. The growth in the global cross-border e-commerce is expected to increase future demand for the air cargo industry. In particular, The Asia-Pacific region, which

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accounted for 37% market share is identified as a biggest emerging region for the air e-commerce market (Air Freight Industry, 2018).

The benefits of air cargo are its reliability, safety, security and speed especially over long distances. It is an important catalyst of globalization, as it supports the global trade and allows the set-up of complex just-in-time supply chains. However, to continue to compete effectively with other modes of transport, the air cargo industry must ensure that the service benefits of air transportation warrant the price premium charged.

Economic activity has the primary influence on world air cargo development. After a slow recovering from the global financial crisis in 2008, the air cargo fully recovered in 2017. Roughly 56 million tonnes of freight were carried in 2017. Growth of scheduled total freight traffic, expressed in terms of scheduled total freight tonne-kilometres performed (FTKs), was at 9.5% in 2017. This growth is significantly higher than the 3.6% recorded in 2016 (WorldACD, 2018).

However, airfreight demand slowed in 2018 but still increased by 4.5% (ICAO, 2018). Although international e-commerce continues to grow, there were signs of weakness in global economic activity (IATA, 2019). One of the reasons for the decline in cargo volumes in 2018 is partly the result of the ongoing trade war between the United States (US) and China (WorldACD, 2018). More precisely, the China-US trade route registered a decrease of 5% and in the opposite direction there was an 8% fall (WorldACD, 2018). Abbeit significantly smaller, five of the six regions reported year-on-year demand growth in 2018 – Asia Pacific, Europe, North America, Middle East and Latin America (Figure 1). After a few years of positive developments in Africa, the freight traffic decrease in 2018 as demand conditions on all key markets to and from Africa “remain weak” (IATA, 2019). North American airlines recorded the fastest growth of any region with an increase in demand of 3.1% year on year. Once again the strength of the US economy and consumer spending has helped support the demand for air cargo over the past year, benefiting US carriers. Unlike their across-the-ocean neighbours, European airlines experienced a reduction in freight demand of 0.2% in comparison to the 2017 as weaker manufacturing conditions for exporters, and shorter supplier delivery times particularly in Germany, impact the demand. Middle Eastern airlines’ freight traffic stayed stable and recorded the increase by 1.7% in 2018 (IATA, 2019).

2. AIR CARGO INDUSTRY – OVERVIEW

Air cargo services are provided by a several group of airlines that offer differing services based upon wide ranging customer demands. Generally, there are four basic types of airlines that provide these services:

- Integrated express operators - operate a fleet of scheduled aircraft, trucks, and couriers offering door-to-door delivery service;
- All-cargo airlines - dedicated to air cargo transport;
- Scheduled passenger airlines - transport freight as a way of filling up spare capacity on their passenger aircraft;
- Cargo charter airlines - unscheduled air charter operators who transport freight from airport-to-airport.

It is a common practice in many industries that competition is based on demand or price. However, in air cargo market, multi-dimensional competition comprising
promised delivery time (PDT) and demand/price is of great practical significance (Wang et al., 2017). Delivery logistics (i.e. PDT) is an important competitive factor (Wen et al., 2011) to evaluate service quality. By definition, PDT is the sum of loading and unloading time, inventory time, airport processing time, waiting time and flight time (Feng et al., 2015b). Many air cargo carriers, especially the express carriers, make efforts to shorten delivery time and provide delivery service with time guarantee.

![Graph showing scheduled international freight tonne kilometres annual growth by region (2015-2018)](source: IATA, 2019)

All-cargo airlines and scheduled passenger airlines are major general cargo operators and coexist in some markets. However, together with the growth of air cargo market, integrated express operators for years expand their worldwide service network and scale and aggressively develop hub-and-spoke network for efficient delivery.

Even if the first effect of deregulation and growing demand for air cargo services was the emergence of new cargo airlines, very soon many airlines began to merge resulting in high concentration of the contemporary airline cargo industry (Pavlović and Babić, 2018). The distinction between express and general air cargo continues to blur. Traditional providers are expanding their time-definite offerings, and express carriers, cargo airlines, and postal authorities are consolidating. The acquisition of TNT by FedEx will further change the competitive environment of the express industry (FedEx, 2016).

The growing demand for air cargo transportation services has opened new challenges for the service providers. Airlines are challenged to manage their air cargo operations efficiently by developing strategic operation plans that allow these airlines to promptly adapt and respond to changes in the global competitive environment. Triggered by rising fuel cost and trade growth, they need to be focused on implementing fuel-efficient solutions and accommodate innovative technologies to provide cost-effective services.

The efficiency of the airline, as in other industries, is measured as the ratio of output produced per unit of input. The goal is to achieve the highest economic result (output)
with the lowest possible economic investment (input). In other words, efficiency could be defined as ability to fulfil determined goals with minimal utilization of available resources.

The objectives of the present paper are to explore the operational performances and efficiency of leading air cargo airlines in the world market. To carry out our research, the survey data are collected and the most relevant parameters are identified. The selected data are grouped as inputs and outputs and the comparative performance of selected cargo airlines is analysed by employing the data envelopment analysis (DEA). Furthermore, in order to improve the basic DEA model that allows us to estimate not only efficiency measures but also the preference weights, we proposed weighted DEA model. The weights for this model are determined by the Analytic Hierarchy Process (AHP). This paper, for the first time, proposes a novel AHP-DEA approach to measure efficiency of cargo airlines. By determining the performance of the cargo airlines' operations one can get further insights from the obtained results and can develop appropriate policy for further improvement of the operational performance.

After the introduction and literature review, the AHP-DEA research methodology, including both basic and weighted DEA models, is presented. The appropriate inputs and outputs are proposed and pairwise matrices are created based on authors' knowledge. Further, the data are described and comparative analysis of DEA models is provided. The results are discussed and followed by concluding remarks.

3. LITERATURE REVIEW

DEA is one of the most popular a non-parametric approach to measure efficiency of comparable organizational units with common inputs and outputs. DEA model is introduced by Charnes, Cooper, and Rhodes (1978), and built upon the efficiency frontier model of Farrell (1957). This model is commonly known as CCR model, which can be presented in two basic variants, i.e. input-oriented and output-oriented. Another also popular DEA model is introduced by Banker, Chames and Cooper (1984) and it is known as BCC model. Unlike the CCR model that measures efficiency assuming constant returns to scale (CRS), the BCC model allows for variable returns to scale (VRS).

There are many papers in the academic literature that deal with the productivity and efficiency analyses in the airline industry using DEA. One of the first works in the estimation of efficiency in the airline industry applying DEA is done by Schefcicky (1993). The author explores key strategic determinants of high profitability and performance based on the comparison of international airlines. Moreover, regression analysis is employed in order to analyze relationship between profitability and performance by considering efficiency. Good et al. (1995) employ both DEA method and Cobbe-Douglas econometric model to examine the efficiency of the largest European and American airlines in the period which coincides with the process of deregulation and liberalization of the air transport markets.

Scheraga (2004) uses the CCR DEA model for the purpose of assessing the efficiency for 38 international airlines in the time period from 1995 to 2000. He studied pre- and post-9/11 terrorist attack effects on operational and financial efficiency of international air carriers. Chiou and Chen (2006) implement both CCR and BCC basic DEA models, in order to evaluate the performance of Taiwanese domestic air routes from the
perspectives of cost efficiency, cost effectiveness and service effectiveness during the year 2001.

Assaf and Josiassen (2011) apply an output-oriented BCC DEA model with efficiency score bootstrapping, for the purpose of assessing the performance of 15 UK-based air carriers for the period 2002–2007. Merkert and Morrell (2012) implement both CCR and BCC basic DEA models with input orientation, in order to evaluate the efficiency of international and European air carriers. Jain and Natarajan (2015) and Sakthidharan and Sivaraman (2018) investigate the technical and scale efficiency of Indian airlines for different time period. They use the VRS model of DEA with two inputs and two and more outputs. Airline efficiency performance in the turbulent period before and after economic crisis is presented by Kuljanin et al. (2017). Hong et al. (2018) use a three-stage model, applying DEA in the first stage to calculate airline efficiency in the period 2008-2015. The authors take four different methods such as CRS and VRS with input and output orientation to give different DEA airline efficiency measures for each year.

It should be noted (from the abovementioned literature review) that basic DEA has been applied as standalone technique in many studies that evaluate efficiency of different airlines in different time period. Moreover, there have been a vast number of studies that used some modification of the standard DEA approach combined with different techniques. Barbot et al. (2008) apply DEA approach combined with the Total Factor Productivity index. The Malmquist index is combined with modified DEA by Chow (2010). He employs the CCR input-oriented DEA model attempting to evaluate the efficiency of Chinese airlines. The author investigates the association of airline ownership status with efficiency, comparing the productive efficiency of state-owned and privately-owned Chinese airlines for different time periods. The study shows that privately-owned airlines have exceeded state-owned airlines in terms of productive efficiency. Further, some modification of the standard DEA approach are combined with regression models (Greer, 2009; Barros and Peynoch, 2009), Tobit model (Fethi et al., 2000; Bhadra, 2009), the two-stage DEA approach, with partially bootstrapped random effects Tobit regressions in the second stage (Merkert and Hensher, 2011), the B convex DEA model (Barros et al., 2013), and fuzzy logic in a fuzzy-based DEA approach (Kuljanin et al., 2019). Kottas and Madas (2018) provide the comparative efficiency analysis of major international airlines using an integrated methodological framework employing DEA with super-efficiency and intertemporal approach. Considering above-mentioned literature, it can be seen that efficiency of cargo airlines are not represented in the literature to the appropriate extent.

The noticeable issue is that DEA approach is combined with the AHP in different ways and in different fields (Sinuany-Stern et al., 2000, Yang and Kuo, 2003; Lozano and Villa, 2009, Lai et al., 2015; Dožić and Babić, 2015, etc.). More precisely, two main ways could be distinguished: DEA could be applied firstly in order to determine efficient units, and AHP to rank them, or AHP could be employ firstly to determine weights which will be incorporated in DEA model. Besides the fact that DEA and DEA in combination with AHP have successful application in different fields, it can be seen, in view of the cited literature, that DEA-AHP has not been used for evaluating cargo airlines efficiency yet. Bearing in mind that efficiency is crucial issue for the airlines operating in the changeable market, and the fact that DEA is very effective method for evaluating efficiency, the authors decided to employ it with the AHP in this paper.
4. RESEARCH METHODOLOGY

Our approach to the problem of measuring the efficiency of leading cargo airlines can be illustrated by Figure 2. At the beginning, appropriate inputs and outputs should be defined to reach the final goal, i.e. to determine and analyze the efficiency of leading cargo airlines. Once inputs/outputs have been selected the DEA should be applied in the basic model, or weights for inputs/outputs should be determined in the weighted DEA model. The basic model would enable to distinguish efficient and inefficient cargo airlines, while weighted DEA model would pointed out the efficient airlines based on the significance of each input and output which is determined by their weights. Moreover, both models would enable a benchmark and cargo airlines ranking and further enable offering the directions for improving the efficiency of inefficient airlines.

The following sub-sections explain the inputs and outputs selection, application of AHP to derive inputs and outputs weights and DEA models. In Section 5 the proposed models for measuring leading cargo airlines efficiency are applied to the leading world cargo airlines.

4.1. Selection of inputs and outputs

In order to assess and optimize the airline productivity in air cargo transport, we should identify the most relevant parameters which should be taken as inputs and outputs. Depending on airline business model (full service or low-cost, scheduled or charter, passengers or cargo) and its mission on the market, different parameters are considered. In line with previous researches, it is noted that the major trade-off in airline management is between capital and labour. Finally, we selected the number of employee, number of aircraft in the fleet and available freight tonne-kilometres (AFTK) as three inputs, while the freight tonne-kilometres (FTK) and revenue are selected as two outputs to reflect the cargo airlines efficiency. In both DEA models the same three input factors and two output factors are used.

*The input parameters:* Number of employee ($I_1$) is considered as input parameter and it is used by many authors (Chow, 2010; Merkert and Hensher, 2011; Barros et al., 2013, etc.). Number of aircraft in the fleet ($I_2$) represents the size of the airline's fleet. It should be noted that this parameter does not indicate the size of the aircraft, but only the size of the fleet. However, it is still used in DEA studies (Barbot et al., 2008; Barros and Peypoch, 2009). Available freight tonne-kilometres ($I_3$) represent the available capacity of an airline in tonnage and it is commonly used in similar researches (Schefczyk, 1993;
Scheraga, 2004; Jain and Natarajan, 2015; Sakthidharan and Sivaraman, 2018; Kuljanin et al. 2019). It is measured as the sum of the product of weight capacity (in tonnes) multiplied by distance covered (in kilometres) for each flight.

The output parameters: Freight tonne-kilometres ($O_1$) represent the realized traffic and it is calculated as the sum of the product of freight carried (in tonnes) multiplied by distance covered (in kilometres) for each flight. Actually, one FTK is one metric tonne of revenue load, carried one kilometre. This measure represents non-passenger traffic related output for the industry (used by Scheraga, 2004; Barbot et al., 2008; Merkert and Hensher, 2011, etc.). Revenue ($O_2$) is measured in monetary units, more precisely in millions of United States Dollars (USD), and it is calculated for one year. This measure is in line with several studies e.g. Merkert and Morrell (2012), Barros et al. (2013).

Once we defined inputs and outputs, we can proceed with the DEA models and AHP weights calculation.

4.2. Proposed DEA models

The efficiency in DEA model is measured based on two components: the technical efficiency which estimates how best the inputs are converted to outputs, and the scale efficiency which describes the deviation from the most efficient scale size for a unit under consideration. The unit under the consideration in DEA terminology is defined as Decision Making Unit (DMU). The main assumption in CCR model is that the unit operates at constant returns to scale (CRS). DEA model calculates the weights that can be assigned to the input and output for the DMU to achieve the best efficiency within the specified constraints. It should be noted that a DMU found to be efficient by DEA is only efficient relative to the other DMUs in the study and does not imply that an efficient DMU is efficient in all respects in its individual capacity. The efficiency determined by DEA depends on the number of DMUs included in analysis, as well as on the number and the structure of inputs and outputs. The desired number of DMUs should be three times the number of inputs and outputs for better discrimination in a standard DEA formulation (Cooper et al., 2007).

In DEA model with multiple inputs and multiple outputs, efficiency is the ratio of the weighted sum of outputs to the weighted sum of inputs. The weights for the inputs and outputs for each DMU are calculated in order to maximize the efficiency of the considered DMU while restricting the efficiencies of the other DMUs within 0 and 1. The basic DEA model with $n$ DMUs in which each has $i$ inputs and $r$ outputs for assessing the relative efficiency of $k$-th DMU is presented by (1).

$$\begin{align*}
\max \quad & h_k(u,v) = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \\
\text{s.t.} \quad & \sum_{r=1}^{s} u_r y_{rk} \leq 1, j = 1, 2, ..., n \\
& \sum_{i=1}^{m} v_i x_{ik} \leq 1, j = 1, 2, ..., n \\
& u_r \geq 0, r = 1, 2, ..., s \\
& v_i \geq 0, i = 1, 2, ..., m
\end{align*}$$

(1)
where $h_k$ denotes relative efficiency of $k$-th DMU, $n$ is the number of considered DMUs, $s$ is number of outputs, $m$ the number of inputs, $u_r$ is weight for the output $r$, $v_i$ is weight for the input $i$.

As abovementioned, DEA is usually implemented in two forms, i.e. input-oriented and output-oriented. Input-oriented CCR model (input minimization model) determines the relative efficiency of a DMU by analyzing how efficiently the inputs are utilized to produce the given output. On the other hand, the output-oriented CCR model (output maximization model) estimates the relative efficiency of a DMU in order to determine the optimal amount of output to be produced for the considered input combination. Chosen cargo airline outputs explained in terms of FTK and revenue are not factors that can be influenced by the airline management. However, selected input factors (number of employee, number of aircraft and AFTK) can be controlled by the airline. Thus, the input minimization model of DEA (CCR) is used for this study.

A general input-oriented CCR model expressed in the following linear programming form (2):

\[
\begin{align*}
\min & \quad \sum_{i=1}^{m} v_i x_{ik} \\
\text{s.t.} & \quad \sum_{r=1}^{s} u_r y_{rk} = 1 \\
& \quad \sum_{r=1}^{s} u_r y_{rk} - \sum_{i=1}^{m} v_i x_{ik} \leq 0, \quad k = 1, \ldots, n \\
& \quad u_r, v_i \geq \varepsilon; \quad r = 1, \ldots, s; \quad i = 1, \ldots, m
\end{align*}
\]

where $\varepsilon$ is a non Archimedean infinitesimal introduced to insure that all the factor weights will have positive values in the solution. A DMU is considered to be efficient if it has an efficiency score of 1 and inefficient if it has efficiency score less than 1.

In order to improve results gained by basic DEA model, we proposed weighted DEA model where the weights were obtained through AHP approach. Integration of DEA and AHP is not novel (Sinuany-Stern et al., 2000; Yang and Kuo, 2003; Wang et al., 2008; Lai et al., 2015), but, to the best of our knowledge, it has not been applied to the cargo airlines efficiency evaluation. The first step is to apply the AHP method to determine input/output weights, and then to use these results in weighted DEA model. Having explained the conceptual definition of DEA we proceed next to the explanation of inputs/outputs weights calculation by AHP.

4.3. Inputs/outputs weights calculation by AHP

AHP is a multi-criteria decision-making approach which decomposes the problem into a hierarchy of issues which should be considered (Saaty, 1980). It presents a theory of measurement through pairwise comparisons made using a scale of absolute judgments. The absolute judgements represent the domination measure of one element over another with respect to a given attribute. In order to enable comparison of alternatives and criteria Saaty (1980) introduced a fundamental scale which indicates the intensity of importance on an absolute scale. Pairwise comparison matrices for criteria and alternatives enable computing of local and global priorities as well as ranking of alternatives.
In this research AHP is used to determine the significance of the inputs and outputs parameters for weighted DEA model. In order to achieve the goal and find the efficient cargo airlines, the problem is structured as four-level problem (Figure 3). After the overall goal which is set in the first level, inputs and outputs are set in the second level of hierarchy. The third level includes input parameters (number of employee, number of aircraft and offered capacity) considered as sub-criteria of input, as well as output parameters (realized traffic and total revenue) considered as sub-criteria of output. The fourth level could include different cargo airlines selected to be candidates in the set of alternatives, but it is not considered in this research. Moreover, instead to finish the AHP procedure and determine the global priorities (which determine rank of airlines), the local priorities (relative importance of inputs and outputs over each other) are calculated. Furthermore, using the local priorities it is possible to compute the ratio of different inputs, as well as ratios of selected outputs, which are needed in defining significance of the inputs and outputs parameters for weighted DEA model.

Priorities from pairwise comparison matrices can be derived in different ways using: eigenvector method, geometric mean method or arithmetic average method. In this research, the eigenvector method is used to determine weights of the input and output parameters for DEA models. The priorities of the elements can be estimated by finding the principal eigenvector \( w \) of matrix \( A \), \( AW=\lambda_{\text{max}}W \), where \( \lambda_{\text{max}} \) is maximum eigenvalue of the matrix \( A \) (Saaty, 1980). Since the pairwise comparisons are not perfectly consistent, consistency should be checked by calculating consistency ratio (CR) as ratio of Consistency Index (CI) and Random Index (RI). Inconsistencies are acceptable and a reliable result may be expected if \( CR<0.1 \). Random Inconsistency Index (RI) for small problems is adopted in accordance with Saaty (1980) and Saaty (1990), while consistency index is calculated as \( (\lambda_{\text{max}} - n)/(n - 1) \).

To derive the weights, sometimes it is possible to use the other techniques (fuzzy AHP, or other multi-criteria decision making techniques), but sometimes the technique is determined on the basis of the data availability (Dožić and Kalić, 2018; Dožić et al., 2018). AHP befits better in the case when pairwise comparison of the data are available, while fuzzy AHP can use imprecise pairwise comparison, which is suitable for cases when decision makers do not. comparisons.
5. DATA AND MODELS APPLICATION

5.1. Data

In this research we use the data of 18 largest cargo airlines (DMUs) in the world for the year 2017 (Table 1). Having in mind that our DEA models use three inputs and two outputs, the number of cargo airlines is in accordance with the DEA rule related to desired number of DMUs.

The research draws data from various sources (sample airline annual reports, IATA (2018), web sites of cargo airlines, etc.). We focused on the cargo airlines that are ranked as leaders in the world based on total freight tonne-kilometres, which allows a robust sample for analysis. This sample encompasses three North American airlines, five airlines from Europe (including Turkish Airlines), three airlines from Middle East and seven from Asia Pacific region.

Table 1. Cargo airlines input-output data for 2017 and descriptive statistics

| Cargo Airlines                      | $I_1$  | $I_2$  | $I_3$ (mil) | $O_1$ (mil) | $O_2$ ($\text{mil}$) |
|-------------------------------------|--------|--------|-------------|-------------|---------------------|
| FedEx Express                      | 208046 | 657    | 33702       | 16851       | 5037                |
| Emirates SkyCargo                  | 48807  | 112    | 24570       | 12715       | 27879               |
| UPS Airlines                       | 21312  | 581    | 23880       | 11940       | 65872               |
| Cathay Pacific Cargo               | 22706  | 63     | 17163       | 10772       | 12399               |
| Qatar Airways Cargo                | 31889  | 86     | 21998       | 10999       | 11597               |
| Korean Air Cargo                   | 20363  | 72     | 10031       | 8015        | 312                 |
| Lufthansa Cargo                    | 4500   | 239    | 12867       | 7317        | 2882                |
| Cargolux                            | 3463   | 27     | 12102       | 7322        | 2264                |
| Singapore Airlines Cargo           | 841    | 40     | 11127       | 6592        | 2220                |
| Air China Cargo                    | 5200   | 226    | 13319       | 6701        | 1522                |
| China Southern Airlines            | 6791   | 261    | 13074       | 6174        | 18910               |
| China Airlines                     | 12645  | 40     | 7961        | 5741        | 42970               |
| Air Bridge Cargo Airlines          | 1300   | 18     | 7919        | 5543        | 846                 |
| All Nippon Airways                 | 13986  | 86     | 6800        | 4810        | 312                 |
| Turkish Airlines                   | 24075  | 120    | 5910        | 4728        | 1317                |
| British Airways                    | 40680  | 98     | 8899        | 4364        | 900                 |
| Etihad Airways                     | 24558  | 42     | 9562        | 4303        | 900                 |
| United Airlines                    | 88531  | 248    | 13929       | 4249        | 1035                |
| Max                                 | 208046 | 657    | 33702       | 16851       | 65872               |
| Min                                 | 841    | 18     | 5910        | 4249        | 312                 |
| Average                            | 32205  | 167    | 14156       | 7729        | 14158               |
| SD                                  | 47455  | 177    | 7217        | 3434        | 21232               |

The sample consists of two integrated express operators, 14 schedule passenger and two all-cargo airlines. Three of 14 schedule passenger airlines transport the freight exclusively using belly hold of the passenger aircraft (All Nippon Airways, British
Airways and United Airlines). The rest of the scheduled passenger airlines are using both cargo and passenger aircraft for freight transportation. In order to make different fleets comparable, we weighted the passenger fleet of schedule passenger airlines. Namely, based on relevant data related to carried freight and available capacity of the passenger aircraft and assumption that the belly holds of passenger aircraft are always full, we estimated the share of belly hold capacity in total available capacity. Therefore, we assume that this ratio is approximately $\frac{1}{3}$. Thus, the real number of aircraft in the fleet used in models represents the sum of number of cargo aircraft and $\frac{1}{3}$ of the number of passenger aircraft.

Table 2. Data correlation matrix

|     | $I_1$ | $I_2$ | $I_3$ | $O_1$ | $O_2$ |
|-----|-------|-------|-------|-------|-------|
| $I_1$ | 1     |       |       |       |       |
| $I_2$ | 0.651 | 1     |       |       |       |
| $I_3$ | 0.690 | 0.716 | 1     |       |       |
| $O_1$ | 0.586 | 0.604 | 0.938 | 1     |       |
| $O_2$ | 0.491 | 0.736 | 0.710 | 0.709 | 1     |

A correlation matrix for input/output data is presented in Table 2. The medium level of correlation can be observed for selected inputs and outputs.

5.2. AHP application

Pairwise comparison matrices for the AHP are designed based on the authors’ knowledge and experience, and they are presented in Tables 3-5, as well as appropriate local priorities. It should be noticed that the consistency is on the required level.

Table 3. Pairwise comparison matrix for the first level

| Input | Output | Local priorities |
|-------|--------|------------------|
| Input | 1      | $\frac{1}{2}$   | 0.3333           |
| Output| 2      | 1                | 0.6667           |

$\lambda_{max}=2$  $CI=0$

Table 4. Pairwise comparison matrix for the inputs

| Inputs | $I_1$ | $I_2$ | $I_3$ | Local priorities |
|--------|-------|-------|-------|------------------|
| $I_1$  | 1     | 2     | $\frac{1}{3}$ | 0.2297           |
| $I_2$  | $\frac{1}{2}$ | 1     | $\frac{1}{5}$ | 0.1220           |
| $I_3$  | 3     | 5     | 1     | 0.6483           |

$\lambda_{max}=3.00369$  $CI=0.0018473$

In order to calculate importance of inputs and outputs we multiply local priorities of the inputs by local priority of input from the first level, and local priorities of the outputs by local priority of output determined from the first level. Finally, the importance of inputs and outputs are derived and their values are shown in Table 6.
The values from the Tables 4-5 are further used to calculate ratios $I_1/I_2$, $I_3/I_1$ and $I_3/I_2$, as well as $O_2/O_1$, which are 1.88, 2.82, 5.31 and 2, respectively. These ratios are used for weighted DEA model in order to improve the results obtained by basic DEA model. Although it would be interesting to see how the pairwise comparison changes influence the weights and the final results, the sensitivity analysis is not carried out due to the space limitation of this paper.

6. RESULTS AND DISCUSSION

6.1. Basic DEA model

The results for basic DEA model with input-oriented CCR specification are obtained by using DEA-Solver software (learning version 8.0) and are presented in Table 7. The efficiency scores with CCR model assuming CRS shows that there are five efficient cargo airlines (Korean Air Cargo, Singapore Airlines Cargo, China Airlines, Air Bridge Cargo Airlines and Turkish Airlines) and they are thus potential reference units. These five cargo airlines shape the empirical frontier and this is the maximum possible efficiency that any of the inefficient cargo airlines can achieve in any level of inputs (for the observed population). In comparison with these airlines, all other airlines are found inefficient. According to the results, cargo airlines from Asia are more efficient than the cargo airlines from other regions. The minimum efficiency is 38.14% for DMU number 18. This means that United Airlines would have to decrease its inputs by 61.86% in order to become efficient. The mean efficiency score is 80.9%, i.e. 19.1% inefficiency, and the standard deviation is 17.72%.

In Table 7 (fifth column) the presented values are only determined for inefficient cargo airlines. These results represent references that can be used to provide the inefficient cargo airline information on which efficient airline it is compared to. In other words, to provide the information for inefficient airline which example of best cargo airlines they should follow. For example, the inefficient airline FedEx Express is compared to efficient airlines numbered 12 and 15. According to the numbers in brackets that represent intensity variable, the airline 15 (Turkish Airlines) is the most relevant DMU for the FedEx Express, since it has the highest value. For efficient cargo airlines the value in fifth column represents the number of the airlines for which this airline is benchmark. China Airlines is a benchmark for the largest number of cargo airlines (11 airlines).

A first observation in Table 7 is low efficiency for FedEx Express, which is the largest cargo airline in terms of FTK (Table 1). It is an integrated airline and this result is in contrast with the fact that this type of operators is currently considered among the best operators in air cargo industry with major market share. UPS Airlines performs better than FedEx Express in terms of estimated efficiency; however, it was not found the place among efficient airlines. Their low efficiency score in this study can be explained by the fact that the nature of their business and specific door-to-door service, usually within a stated time limit, demands the use of relatively more inputs to produce certain output.
In this way they can guarantee sufficient spare capacity. Thus, this type of efficiency measures, when only the resource utilization and cargo operations are considered, do not fit their service operation and do not give a true picture of their business success.

Table 7. Results for basic DEA model

| No. | DMU                  | Score (%) | Rank | Benchmarks                      | Improvements (%) | Slack |
|-----|----------------------|-----------|------|---------------------------------|------------------|-------|
|     |                      |           |      |                                 | I₁   | I₂   | I₃   | I₁   | I₂   | I₃   |
| 1.  | FedEx Express        | 62.53     | 15   | 12 (1.344); 15 (1.932)          | -69  | -57  | -34  | 73030| 146  | 0    |
| 2.  | Emirates SkyCargo    | 70.29     | 13   | 6 (0.525); 12 (0.623); 13 (0.89)| -60  | -30  | -30  | 14585| 0    | 0    |
| 3.  | UPS Airlines         | 91.39     | 6    | 9 (0.499); 12 (1.507)           | -9   | -86  | -27  | 0    | 451  | 4278 |
| 4.  | Cathay Pacific Cargo | 86.76     | 9    | 6 (0.308); 12 (0.259); 13 (1.23)| -51  | -13  | -13  | 8559 | 0    | 0    |
| 5.  | Qatar Airways Cargo  | 68.62     | 14   | 6 (0.395); 12 (0.24); 13 (1.164)| -60  | -31  | -31  | 9285 | 0    | 0    |
| 6.  | Korean Air Cargo     | 100       | 1    |                                 |                  |       |
| 7.  | Lufthansa Cargo      | 80.31     | 11   | 6 (0.076); 12 (0.043); 13 (1.165)| -20  | -88  | -20  | 0    | 164  | 0    |
| 8.  | Cargolux             | 90.22     | 7    | 12 (0.027); 13 (1.293)          | -42  | -10  | -14  | 1099 | 0    | 465  |
| 9.  | Singapore Air. Cargo | 100       | 1    |                                 |                  |       |
| 10. | Air China Cargo      | 70.72     | 12   | 6 (0.106); 12 (0.013); 13 (1.042)| -29  | -88  | -29  | 0    | 133  | 0    |
| 11. | China Southern Airlines| 83.54 | 10   | 9 (0.579); 12 (0.41)            | -16  | -85  | -26  | 0    | 178  | 1211 |
| 12. | China Airlines       | 100       | 1    |                                 |                  |       |
| 13. | Air Bridge Cargo Air. | 100     | 1    |                                 |                  |       |
| 14. | All Nippon Airways   | 88.53     | 8    | 6 (0.592); 15 (0.013)           | -11  | -49  | -11  | 0    | 32   | 0    |
| 15. | Turkish Airlines     | 100       | 1    |                                 |                  |       |
| 16. | British Airways      | 61.41     | 16   | 6 (0.38); 12 (0.006); 15 (0.272)| -65  | -39  | -39  | 10631| 0    | 0    |
| 17. | Etihad Airways       | 60.62     | 17   | 6 (0.246); 12 (0.009); 13 (0.412)| -77  | -39  | -39  | 9236 | 0    | 0    |
| 18. | United Airlines      | 38.14     | 18   | 6 (0.101); 15 (0.728)           | -78  | -62  | -62  | 14193| 0    | 0    |

In contrast to integrated cargo airlines, schedule passenger airlines show better results in this study. Namely, four out of five airlines identified as an efficient by the DEA model are schedule passenger airlines. These two types of airlines differ a lot in size, type of operations and the service offered. In terms of operation efficiency, it can be concluded that combining the passenger and cargo transportation on the same or dedicated fleet, airlines can perform better efficiency scores. Among the schedule passenger airlines, there are few of them (e.g. Emirates SkyCargo and Qatar Airways Cargo) which are also leading cargo airlines in terms of FTK, but show low efficiency results. This can be explained by the fact the Gulf airlines are generally enjoy the substantial supportive policies of their governments, which are reflected in the form of lower operation costs and lower labour cost in comparison to the market conditions in other regions.

All-cargo airlines show high efficiency scores. Namely, Air Bridge Cargo Airlines is recognized as an efficient airline and represent the benchmark for even seven airlines. Cargolux, one of the leading cargo airlines in Europe showed the efficiency score of more than 90%. Obviously, the decision to perform only the flying operation for cargo transportation (unlike integrated cargo operators) brings some benefits on the operational side of the cargo business for these airlines.
Finally, in the columns six, seven and eight of the Table 7 we provide the relevant calculations for inefficient DMUs. Those values are determined based on the intensity variables. The data show the size of inefficiency of the examined DMUs in relation to the reference cargo airlines. Furthermore, these values are determined in accordance with the DEA orientation, i.e. they indicate the direction that an inefficient cargo airline approaches to the efficient frontier. In particular, how much is needed to reduce the input levels while maintaining the same level of outputs. For example, in order to become efficient FedEx Express should reduce the number of employees for 69%, fleet size for 57% and offered capacity for 34%. The results also show that this correction in not enough for inefficient airlines to reach the efficient frontier, so further improvement can be made by using the slack variables. The values of slack variables are showed in the last three columns of Table 7.

6.2. Weighted DEA model

Basic DEA model determine the efficient DMUs based on the output/input ratios. If a DMU has at least one of these ratios ranked as the best one, then that DMU will be identified as efficient. This will happen even if all other ratios for that DMU are not good or are recognized as very inefficient. For example, according to basic DEA, Korean Air Cargo is efficient based on $O_1/I_3$ ratio, but its other ratios are very low. In order to improve the results obtained by basic DEA model, we introduced the weights derived from AHP in weighted DEA model. New results are shown in Table 8.

| No. | DMU                     | Score (%) | Rank | Benchmarks | Improvement (%) | Slacks |
|-----|-------------------------|-----------|------|------------|----------------|--------|
| 1.  | FedEx Express           | 40.78     | 15   | 12 (1.73)  | -89 -89 -59    | 61962 755 |
| 2.  | Emirates SkyCargo       | 31.72     | 10   | 12 (0.98)  | -86 -84 -44    | 2682 220 |
| 3.  | UPS Airlines            | 85.61     | 3    | 12 (1.65)  | -57 -41 -47    | 431    |
| 4.  | Cathay Pacific Cargo    | 33.51     | 9    | 12 (0.62)  | -81 -75 -45    | 0 0    |
| 5.  | Qatar Airways Cargo     | 24.06     | 13   | 12 (0.62)  | -75 -71 -78    | 0 0    |
| 6.  | Korean Air Cargo        | 24.40     | 12   | 12 (0.31)  | -84 -70 -74    | 956 71 |
| 7.  | Lufthansa Cargo         | 54.90     | 7    | 12 (0.32)  | -83 -89 -57    | 0 118  |
| 8.  | Cargolux                | 61.94     | 6    | 12 (0.31)  | -83 -80 -86    | 0 4    |
| 9.  | Singapore Airlines Cargo| 91.42     | 2    | 12 (0.28)  | -83 -98 -91    | 0 25   |
| 10. | Air China Cargo         | 42.72     | 8    | 12 (0.27)  | -83 -85 -79    | 0 86   |
| 11. | China Southern Airlines | 77.70     | 5    | 12 (0.57)  | -48 -73 -33    | 0 180  |
| 12. | China Airlines          | 100.00    | 1    | 17         | 0              | 6      |
| 13. | Air Bridge Cargo Airlines| 82.51    | 4    | 12 (0.22)  | -59 -97 -87    | 0 6    |
| 14. | All Nippon Airways      | 21.35     | 14   | 12 (0.18)  | -56 -97 -89    | 619 43 |
| 15. | Turkish Airlines        | 26.65     | 11   | 12 (0.20)  | -44 -97 -88    | 3764 104 |
| 16. | British Airways         | 15.82     | 16   | 12 (0.18)  | -34 -73 -88    | 4051 87 |
| 17. | Etihad Airways          | 14.53     | 17   | 12 (0.17)  | 65 -62 -83     | 1270 48 |
| 18. | United Airlines         | 10.01     | 18   | 12 (0.18)  | 171% -82 -87   | 6444 125 |

It can be seen that the number of efficient airlines is reduced from five to only one airline – China Airlines. This is in line with the results obtained in basic DEA model.
where this airline is the benchmark for the largest number of airlines. In this model, China Airlines determines the efficient frontier. The efficiency of the sample is in wider range from 10.01% (United Airlines) to 100% (China Airlines) comparing with basic DEA. The mean value is equal to 45.31%, which is lower than in basic model, while the standard deviation is increased to 30.25.

It is also interesting to note that previously efficient airlines have changed their rank. Namely, Singapore Airlines Cargo is ranked as second with the score of 91.42%, while Air Bridge Cargo Airlines is ranked as fourth, with 82.51% of efficiency. The other two airlines that were fully efficient according to basic DEA model have very low scores according to weighted DEA. Specifically, Turkish Airlines and Korean Air Cargo are at the positions 11 and 12 having 26.65% and 24.4% efficiency, respectively. Further, it means that they need to improve their efficiency by 73.35% and 75.6%, respectively in order to become efficient. This can be explain by the fact that these two airlines have the best load factor ($O_1/I_3$) which qualified them for efficient airlines according to basic DEA. Assigning the weights to inputs/outputs, load factor becomes less important in comparison with the other parameters and pushes these airlines from efficient to the inefficient ones with the very low scores.

From Table 8 can be observed that potential inputs improvements of inefficient airlines are in the wide ranges. For example, potential improvements of $I_1$ vary from shortage of 171% to surplus of 96%, while $I_2$ and $I_3$ have only surplus which is in range 41-98% and 33-91%, respectively. Different efficiency pattern could not be observed based on the type of airlines. In the category of passengers airlines fully efficient as well as airline with the lowest DEA efficiency score can be found. For some cargo airlines (e.g. Cathay Pacific Cargo and Qatar Airways Cargo) the applied improvements are sufficient for achieving the efficient frontier. For the rest of inefficient cargo airlines, additional slacks improvements need to be applied in order to reach the efficient frontier.

7. CONCLUSION

The problem considered in this paper combines two well-known techniques DEA and AHP which have proved to be very useful in solving a variety of problems. Whereas these methods have not been employed to the cargo airline efficiency evaluation yet, we have shown their applicability in this field.

We analysed relevant, available literature and identified the appropriate inputs and outputs. Thus, it is noted that the major trade-off in airline management is between capital and labour and we followed the same concept. The main results from both models imply that the cargo airlines from Asia are more efficient than the cargo airlines from other regions. Moreover, the schedule passenger airlines show better results in efficiency scores in comparison to the integrated operators and all-cargo airlines. Also, the results specify that the most inefficiency of the cargo airlines is due to overstaffing and insufficient fleet utilization.

The results from weighted DEA model, allowed us to reduce the number of efficient cargo airlines from five to one. In this way we avoid a large number of efficient airlines which are actually efficient only due to one parameter performance, while the rest of performances show very poor results.
The key contributions of this research are twofold. The study shows for the first time the individual efficiency score of a large number of cargo airlines. In the existing literature there are some studies about general efficiency estimation in the airline industry, but none of them consider cargo airlines. The second contribution is that we propose the weighted DEA model, where the weights were obtained through AHP approach. Allowing decision maker to design AHP pairwise comparison matrices according to his knowledge and awareness of current and potential future changes on the cargo market, the proposed approach could suggest suitable weights for weighted DEA approach for different “if-then” scenarios based on different assumptions. Since the DEA and AHP usage has an important role in multi-criteria decision making and their application is extensive in a wide variety of areas, this paper shows that the DEA combined with the AHP can be successfully used as a support tool in efficiency evaluation, providing future directions for corresponding improvements.

Future research in this field should include a wider range of inputs and outputs, which will extend the research encompassing both quantitative and qualitative parameters. Moreover, in order to express the criteria importance over each other one can deal with uncertain judgements, which indicates the possibility to use fuzzy sets or fuzzy numbers, and incorporates the vagueness of human thinking.

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