THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

ROUTE BASED PERFORMANCE EVALUATION: AN APPLICATION OF DATA ENVELOPMENT ANALYSIS

Master of Science Thesis

Ömer SAKA

ISTANBUL, 2015

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INDUSTRIAL ENGINEERING

Title of the Master's Thesis	: Route Based Performance Evaluation: An Application of Data Envelopment Analysis
Name/Last Name of the Student	: Ömer SAKA
Date of the Defense of Thesis	: 6 April, 2015

The thesis has been approved by the Graduate School of Natural and Applied Sciences

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This is to certify that we have read this thesis and we find it fully adequate in scope, quality and content, as a thesis for the degree of Master of Arts.

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ACKNOWLEDGEMENTS

I would like to thank my supervisor Prof. Dr. Erkan BAYRAKTAR for his kind support and guidance. I would like to also thank all other faculty members of Bahcesehir University Industrial Engineering Department for their support during my master studies.

I would like to also thank to Prof. Dr. Ahmet BOLAT for his continuous support and guidance in my professional and academic studies and projects.

I wish to express my thanks to my colleague and kind friend, Dr. Zeliha AKÇA for her great ideas and supports to determine the structure of this study.

I would like to also thank to my friend and colleague Bulut ŞENEL for his support and guidance in the preparation of this study.

I owe quite a lot to my family for their support and I would like to dedicate this study to them.

Istanbul, 2015 Ömer SAKA

ABSTRACT

ROUTE BASED PERFORMANCE EVALUATION: AN APPLICATION OF DATA ENVELOPMENT ANALYSIS

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Industrial Engineering

Thesis Supervisor: Prof. Dr. Erkan BAYRAKTAR

April 2015, 45 Pages

This study aims to assess the performance of international flight routes of Turkish Airlines in 2011 by executing their resource allocation and productivity perspective. Data Envelopment Analyses (DEA) is used with its model of Variable Return to Scale (VRS) output oriented method to measure the efficiency of routes with respect to the resources. A total of one hundred and twenty five direct flight routes which are located in different regions and markets are examined. All individual routes are treated as Decision Making Unit (DMU) to evaluate the performance of specific routes. Three variables are selected as input which are ASK (Available Seat Kilometers), Variable CASK (Variable Cost per Available Seat Kilometers) and Cycle. On the other hand, two variables are selected as output which are RPK (Revenue Passenger Kilometers) and RASK (Revenue per Available Seat Kilometer).

Keywords: Data Envelopment Analysis, Route-Based Performance, Decision Making Units

ÖZET

UÇUŞ ROTASI BAZLI PERFORMANS DEĞERLENDİRME:
VERİ ZARFLAMA ANALİZİ UYGULAMASI

Ömer SAKA

Endüstri Mühendisliği

Tez Danışmanı: Prof. Dr. Erkan BAYRAKTAR

Nisan 2015, 45 Sayfa

Bu çalışma tahsis edilen kaynak kullanımı ve verimlilik bakış açısı ile Türk Hava Yolları'nın 2011 yılındaki uluslararası uçuş rotalarının performansını ölçmeyi amaçlamaktadır. Bu uçuş rotalarının performansı değerlendirilirken Veri Zarflama Analizi (DEA) ve bu yöntemin Ölçeği Değişken Getiri (VRS) modeli ile çıktıları arttırmayı hedefleyen bir yaklaşım kullanılmıştır. Farklı bölgelerde ve pazarlarda bulunan uluslararası 125 direkt uçuş rotası incelenmiştir. Her bir rota ayrı ayrı Karar Verme Birimi (DMU) olarak kabul edilerek rotaların performansı değerlendirilmiştir. Bu analizde girdi verileri olarak Arz Edilen Koltuk-Kilometre (ASK), Arz Edilen Koltuk- Kilometre başına Değişken Maliyet (CASK) ve konma sayısı olmak üzere üç değişken kullanılmıştır. Ayrıca, çıktı değişkenleri olarak da Ücretli Yolcu Kilometre (RPK) ve Arz Edilen Koltuk- Kilometre başına elde edilen Gelir (RASK) seçilmiştir.

Anahtar Kelimeler: Veri Zarflama Analizi, Rota-Bazlı Performans, Karar Verme Birimleri

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ABBREVIATIONS

AEA	:	Association of European Airlines
ASK	:	Available Seat Kilometers
BCC	:	Banker, Charnes and Cooper DEA Model
CASK	:	Cost per Available Seat Kilometers
CCR	:	Charnes, Cooper and Rhodes DEA Model
CIS	:	Commonwealth of Independent States
CPT	:	Cape Town International Airport IATA Code
CRS	:	Constant Return to Scale
DEA	:	Data Envelopment Analysis
DEAP	:	Data Envelopment Analysis Computer Program
DMU	:	Decision Making Unit
DRS	:	Decreasing Return to Scale
FRA	:	Frankfurt IATA Airport Code
GRU	:	São Paulo Guarulhos International Airport IATA Code
IATA	:	The International Air Transport Association
IRS	:	Increasing Return to Scale
IST	:	Istanbul Atatürk Airport IATA Code
JFK	:	John F. Kennedy International Airport IATA Code
JNB	:	Johannesburg O. R. Tambo International Airport IATA Code
LHR	:	London Heathrow Airport IATA Code
RASK	:	Revenue per Available Seat Kilometer
RPK	:	Revenue Passenger Kilometers
RPK	:	Revenue Passenger Kilometers
SE	:	Scale Efficiency
TE	:	Technical Efficiency
TFP	:	Total Factor Productivity
TLV	:	Tel Aviv Ben Gurion Airport IATA Code
TXL	:	Berlin Tegel Airport IATA Code
VRS	:	Variable Return to Scale

1. INTRODUCTION

Airline industry has changed considerably in the last decades. De-regulation in Europe, North America and Australia, produced a significant increase in competition. Moreover, economic and political crises also cause many difficulties for airline companies to survive under their previous cost structures. Many of these airlines went bankruptcy or merged and bought by big companies. Furthermore, airlines which were formerly state owned have been either fully or partially privatized to survive under this competitive and customer oriented environment. Likewise, Turkish civil aviation industry also has changed and developed in the last decade or so. Thanks to the political stability and economic improvements in recent years, Turkey has made considerable progress in public air transportation and has become one of the leading countries in air transportation in Europe and in the world. The flag carrier as well as private airline companies have developed in capacity and improved their conditions through competition with others, and have been among the preferred companies for air travel in air travel surveys and rankings. As a result of improvements in the Turkish aviation sector and in contrast to global industry, managerial and operational plans and strategies have become very crucial to compete with others and increase the market share at the global market. For this reason, evaluating airline performance and taking actions according to these evaluations is one of the key points to survive and compete in this competitive environment.

Due to being the national flag carrier and biggest airline company in Turkey, Turkish Airlines' performance evaluation gives a vital understanding of the sector conditions. Turkish Airlines has more than two hundred and thirty aircraft, comprised of different types and models, in its fleet and flies to over two hundred and fifty destinations all over the world. Every year, approximately ten new destinations are being launched in different regions and countries since 2003. Each destination is assigned a certain capacity, frequency, aircraft type and cost of operation which changes with aircraft assignment and flight distance. Moreover, each flight route produces revenue through passengers and cargo operations. Furthermore, Turkish Airlines' network composed of these routes and the contribution of each route effect the overall performance. For this reason, performance of these routes are needed to be evaluated and compared whether the capacity allocated to these routes in the network is right and used efficiently.

This study aims to assess the performance of international flight routes of Turkish Airlines in 2011, which was a very critical term for Turkish Airlines to make a profit while growing organically and inorganically. Evaluating flight routes' performance could allow senior management to understand which route or region has to be focused on and what is the result of their strategic plans in the real world. Moreover, this study also tries to answer these questions; what are the reasons and factors that cause inefficiency? How can the efficiency of the inefficient routes be improved?

Related studies in evaluating the performance of airlines were focused on a whole-company basis. Thus, the improvements suggested by these studies are difficult to be implemented down to each route. Because of different characteristic market condition for each destination and competition at the specific route, its operation plans and management policies had better be established from a route-base view. For this reason, this study is unique and first at the field to evaluate international routes of such a big Airline and try to give new perspective to auditors.

To evaluate the performance of air routes, Data Envelopment Analyses (DEA) is used with its model of BCC or Variable Return to Scale (VRS) output oriented method. A total of one hundred and twenty five non-stop flight routes which are located in different regions and markets are examined. All individual routes are treated as DMUs to evaluate the performance of specific routes. Data envelopment analysis (DEA) is one of the techniques for measuring the relative efficiency of decision making units (DMUs) which perform similar tasks. It is suitable to employ DEA to measure the relative performance of air routes and to propose improvements for the relatively inefficient DMUs. Also, DEA method has been very popular in the recent academic researches to evaluate airline and airport performances. Thus, it is appropriate to use DEA for this study.

The study is organized as follows. In Literature Review section next, the performance issues in aviation sector will be reviewed. In Methodology part, Data Envelopment Analysis will be defined with its graphical interpretation and mathematical formulations. The reasons why to select DEA method to evaluate the performance of air routes will also be discussed. In Data Analysis and Result part, Turkish Airlines' route efficiency will be analyzed by using Data Envelopment Analysis. Also, data, input and output variables will be explained. In the final part, the main findings of the study will be summarized and based on these findings, possible solutions will be presented.

2. LITERATURE REVIEW

This study aims to assess the performance of international flight routes by evaluating their resource allocation from the productivity perspective. There are large number of studies in the air transportation which has applied DEA to evaluate performance, most of them focusing on airlines management and airports operation. Some of these studies are explained below:

Charnes et al. (1996) evaluated the Latin American airlines' domestic and international operations by using DEA method where they applied Multiplicative-DEA model. The authors are emphasized their findings as:

> *"The marginal tradeoffs of the efficient production function are immediately available instead of being harassed by discontinuities of derivatives and numerical instabilities"*

The DEA method was used by Sengupta (1999) to evaluate the performance of seven international airlines. The researcher collected data from Cathay Pacific, Singapore, Quantas, British Airways, American Airlines, KLM, and Japan Airlines between the years 1988 and 1994. Sengupta's findings clearly indicated that changes in both technical and allocative efficiencies among the years 1988-94 had major effect in the air transportation market.

Alder and Golany (2001) used DEA model to select the most efficient networks configurations from the deregulated European Union airline market. In the study, they evaluated the deregulated airline networks' performance by combining DEA with principal component analysis and collecting excessive number of inputs and outputs to overcome DEA difficulties. Surface access to and from hub airports, shopping and common comfort indicators constituted inputs of the model. On the other hand, output measures included profitability, average load factors, average delay and minimum passenger transfer connecting times. This approach can be applicable to evaluate both monetary and quality criteria.

Scheraga (2004) is not only investigated structural drivers of operational efficiency; but also, the author considered airlines' financial conditions on the eve of September 11th. His DEA study calculated the efficiency scores for 38 airlines in the Middle East, Asia, Europe, and North America. The main purpose of the authors study was to find out that notional operational efficiency can related to financial mobility or not. As a result, relative operational efficiency did not related to superior financial mobility. That is why; airline companies prefer their own relatively efficient operational strategies in which they found themselves in fragile positions at financial mobility. That is the reason why the author stated these companies were suffered with the outcomes of September 11th environment.

Chiou and Chen (2006) investigated fifteen Taiwanese domestic air routes in terms of cost efficiency and effectiveness, and service effectiveness by using DEA which was proposed by Fielding et al. (1978). This was the first study to evaluate airline performance considering each route as DMUs not consider whole company basis. They used three different kinds of variables as input, production and service variables to evaluate all of these efficiencies. In their study, there are three input variables stated; fuel cost, personal cost (cabin crew and ground handling crews' salaries), and cost of maintenance, depreciation, interest payments of aircrafts. Number of flights and seat-mile were set as production variables. The service variables included revenue passenger-miles which show the number of miles traveled by paying passengers and embarkation passengers. At the end of their studies, they find out that ten of the routes were relatively cost efficient, five of them were relatively cost effective, and four of the routes were relatively service effective. Clustering analysis was also used to categorize the routes and they clustered routes into four clusters. As a part of the study, clustering analysis helped authors to generate four route clusters based on efficiency scores of fifteen routes in three aspects which are cost efficiency, cost effectiveness and service effectiveness. Authors claim that because of having more routes-depended operating plans and management policies, customers, competitors, and operating environment, it is better to propose a route-base view to evaluate the airline performance.

Lin (2008) made his study based on Chiou and Chen (2006) research about route based performance measurement. He made some comments on their mistakes and errors at their studies. According to his article, they made some mistakes mainly method and variable selection. He claimed that they determine high correlated variables such as passengers-miles which multiply number of passengers by miles, and number of embarkation passengers. He showed the difference of results and wrong evaluation when select one or two correlated variables at the same stage. Also, he point out that their model is not clear at their study because of lack of information. He gave academic and real life example to proof his claims.

Barbot et al. (2008) studied the efficiency and productivity of 49 IATA members by using DEA and total factor productivity (TFP). The study demonstrated that low-cost carriers were more efficient than full service carriers. On the other hand, smaller airlines were worse than larger airlines in terms of efficiency. By considering geographic areas, findings showed that European and American carriers were more efficient than Asia Pacific and China/North Asia airlines. The DEA analysis clarified efficiency and effectiveness are not permanently able to correlate. Other method used in the study, TFP, highlighted uniform in productivity within homogeneous and regulatory structured area such as North America.

Greer (2008) used DEA and the “Malmquist productivity index” to observe productivity alterations of major US airlines by considering the years from 2000 to 2004. As a result of the study, the authors found out significant improvements at the carriers’ productivity in this period. Moreover, productivity enhancements generally occurred at the airlines that were less efficient than the efficient ones which are counted as leader at the field.

Barros and Peypoch (2009) studied 27 member of Association of European Airlines (AEA) to assess the efficiency from 2000 to 2005. In the first stage of the study, it found that almost all 27 of European airline companies have high level of technical and scale efficiency. The second stage of the study aimed to apply bootstrapped truncated regression to mark most important variables of airline efficiency. Furthermore, the result showed that population and network agreements are significantly important in terms of evaluating airline efficiency.

Hong and Zhang (2010) conducted a study to answer whether or not a high degree of cargo business improved the efficiency of operations at mixed passenger/cargo airlines. The DEA led them to analyze operations of 29 specific airlines between the years 1998-2002. The result of DEA illustrated that high degree of cargo businesses are significantly more efficient than low degree ones. In addition to findings, the authors found no statistically significant difference between airlines with similar degrees of cargo business.

Chiou et al. (2011) conducted an empirical study on 1035 routes operated by 37 intercity bus companies in Taiwan. They used data envelopment analysis to measure route efficiency by determining operating revenue and passenger-km as inputs variable; and fuel cost, labor and bus as output variables. Moreover, they set three-stage procedure that determines company efficiency, route efficiency and optimal allocation ratios for the common inputs. They found that the ranking order of company performance determined by the route-based DEA model is identical to that determined by the company-based DEA model. Furthermore, an empirical case demonstrates the superiority of the proposed models in identifying the less efficient routs companies as well as in reducing the input slacks without subjective conjectures

Assaf and Josiassen (2012) evaluated and compared the efficiency and productivity of seventeen European and thirteen United States airlines, over the period from 1999 to 2008. Bayesian distance frontier model was used to measure efficiency scores and productivity. Moreover, they considered both a constrained and an unconstrained model and they also showed the importance of imposing the monotonicity and curvature conditions on the distance function. The efficiency and productivity results based on the constrained model indicate that European airlines have slightly higher efficiency and productivity growth than U.S. airlines. A comparison based on the type of airlines indicates that low-cost airlines are on average more productive and efficient than full-service airlines.

Ha et al. (2013) investigated the effects of downstream airline market structure on airport efficiency. Eleven major airports in Northeast Asia are analyzed based on the sample period of 1994-2011 and their efficiency scores are obtained from both the data envelopment analysis (DEA) and stochastic frontier analysis (SFA). They also applied tobit regression to evaluate the impact of airline concentration, airport governance structure, airport competition and other characteristics on efficiency. The authors found that either too much or too little downstream airline concentration causes airport inefficiency and this shows an inverse U-shaped relationship between airport efficiency and downstream airlines' market concentration.

Barros and Couto (2013) used Luenberger productivity indicator to evaluate productivity changes of 26 European airlines over the period 2000-2011. They also used Malmquist index to compare the change in productivity over the years. They determined the outputs as revenue by passenger kilometer and revenue cargo tones of freight carried; and inputs as number of employees, operational cost and number of seats available. The authors found that most European airlines, except Austrian Airlines, Finnair, Virgin Atlantic, EasyJet and Ryanair, did not experience productivity growth between 2001 and 2011 due to the impact of the external environment, the managerial factors.

Barros et al. (2013) studied on 11 US airlines to investigate their technical efficiency over the period 1998-2010. The B-convex model was preceded in both input orientation and output orientation to test the relationship between airline technical efficiency and the following four correlated variables: international code sharing, airline size, merger and acquisitions and time.

They used total revenue, revenue passenger miles (RPM) and passenger load factor as outputs variable; and total cost, number of employees and number of gallons as inputs variables. The authors found that that US airlines' efficiency can be influenced by the size of the airline, mergers and acquisitions, and by time.

Ahn and Min (2014) studied 23 international airports located different regions during the period of 2006-2011. They used data envelopment analysis to evaluate performance of airports and four input variables and three output variables were selected. The inputs variables are number of runway units, passenger terminal area, and cargo terminal area; while outputs are number of flights, annual passenger throughputs, and annual cargo throughputs. In addition to the DEA, they used the Malmquist productivity index to evaluate the change in airport efficiency over time. The authors found that overall productivity of the international airports has decreased by 1.7% from 2006 to 2011 due in part to government policy changes and technological advances rather than significant improvements in managerial practices.

Lee and Worthington (2014) used the DEA model to measure technical efficiency of 42 airlines in different countries for the year 2006. Moreover, bootstrapped truncated regression model was used at the second stage to explain efficiency drivers. They define three inputs representative of airline operations which are the average number of employees, total assets and kilometers flown; and single output which is available ton kilometers (ATK). In the view of results, authors suggest that;

> *"The mainstream airlines needed to significantly reorganize and rescale their operations to remain competitive. In the second-stage analysis, the results indicate that private ownership, status as a low-cost carrier, and improvements in weight load contributed to better organizational efficiency."*

Zou et al. (2014) investigated the fuel efficiency of 15 US mainline airlines in 2010 using ratio-based, deterministic and stochastic frontier approaches. Moreover, they also investigated efficiency of joint of mainline and its subsidiaries. The ratio-based method was used to calculate fuel consumption per unit mobility output and the frontier approaches were used to evaluate both the mobility and accessibility dimensions of airline production output. The authors found that;

> *"Airline fuel consumption is highly correlated with, and largely explained by, the amount of revenue passenger miles and flight departures it produces. Secondly, depending on the methodology applied, average airline fuel efficiency for the year 2010 is 9–20% less than that of the most efficient carrier, while the least efficient carriers are 25–42% less efficient than the industry leaders. Thirdly, regional carriers have two opposing effects on fuel efficiency of mainline airlines: higher fuel per revenue passenger mile but improved accessibility provision. Moreover, the net effect of routing circuit on fuel efficiency is small. Finally, potential cost savings from improved efficiency for mainline airlines can reach the magnitude of billion dollars in 2010."*

Barros and Wanke (2015) studied on 29 African Airlines to assess the efficiency from 2010 to 2013. They used the TOPSIS technique which is a multi-criteria decision making technique, similar to DEA (Data Envelopment Analysis), ranks a finite set of units based on the minimization of distance from an ideal point, and the maximization of distance from an anti-ideal point. In the first stage of the study, relative efficiency of African Airlines was measured by defining for their inputs as the number of employees, the total number of aircraft, and operating costs, with a negative impact on efficiency levels; for outputs RPK and RTKs with a positive impact on efficiency levels. It found that the average efficiency of African airlines is low in relative terms when they are benchmarked against each other because of some operational procedures adopted by airlines and result of aircraft model used. The second stages of the study, neural networks are combined with TOPSIS results to produce a model for airline performance which has effective predictive ability. The results show that network size-related variables economies of scope, are the most important variables for explaining levels of efficiency in the African airline industry. Furthermore, the authors recommend that if operational procedures are the only reason for having low efficiency then they should be forced to change them to assess the levels of efficiency of African airlines in parallel with their North-American and European counterparts, as a way of achieving a better estimation of the lag in operational practices.

3. METHODOLOGY

In the airline transportation, more than one factor and variable can affect the performance of air routes. To evaluate the performance of each route at wide network carriers such as Turkish Airlines network, multiple input and output variables must be considered in the analysis process. Since each route located in different markets has different characteristics such as competition, addiction of passengers and service level of airline's especially international routes, Data Envelopment Analysis (DEA) was used to evaluate the performance of all network routes and regions at this study.

DEA method has advantages to uniquely consider each route as because routes' operational and financial data sets were very different because of route market. Thus, variety makes route analysis more complex, difficult to evaluate, and needs proper comparison. Therefore, DEA technique is a suitable to analyze them.

Another reason to use DEA at this study is that Turkish Airlines is one of the rapidly growing airlines in the world and therefore every year approximately ten new destinations are launching in different countries and regions. For this reason, input and output data volumes are very different. For instance, Frankfurt (FRA) has been on the air since more than fifty years; however, Sao Paulo (GRU) was launched just few years ago. Therefore, their flight type, stage length, cycle and also administrative functions are very different which is needed to be weighted to compare under same conditions.

DEA technique is also more attractive and popular for the recent academics studies to evaluate airline performance. Except Chiou and Chen (2006) which measured the performance of Taiwan airlines domestic routes with DEA, most of these studies focused on airline overall performance or compare airlines each other. This study is unique and first at the field to evaluate international routes of such a big Airline and try to give new perspective to auditors.

3.1 DATA ENVELOPMENT ANALYSIS (DEA)

Data Envelopment Analysis was established based on linear programing technique to measure efficiency of similar task units' performance which uses the defined inputs to produce defined outputs (Ramanathan, 2003; Silkman, 1986). DEA can be applicable for wide range of similar task units which is also called Decision Making Units (DMUs) such as schools, hospitals, department of companies, bank, airlines and airports. According to Charnes et al. (1978), DEA evaluates the performance of DMUs how to use available resources to produce outputs.

Farrell (1957) was the first researcher worked on the DEA and accepted as the founder of this technique. His study was based on a single input to produce a single output to measure efficiency. Furthermore, Charnes et al. (1978) developed Farrell's study by adding Linear Programing Theory. Multiple inputs and outputs with their related weights can be evaluated at the same time within this perspective. Their study and method is also known as CCR which refers to their first letters of their names (Charnes, Cooper and Rhodes). In 1984, Banker, Charnes and Cooper extend this study with adding convexity constrain to the CCR model formulation to put environmental factors to analyze. This new perspective also called as BCC method. Before giving detail information and explanation about these models, general graphical illustration and mathematical formulation should be mentioned to have better understanding of DEA.

3.1.1 General Assumption and Graphical Illustration of DEA

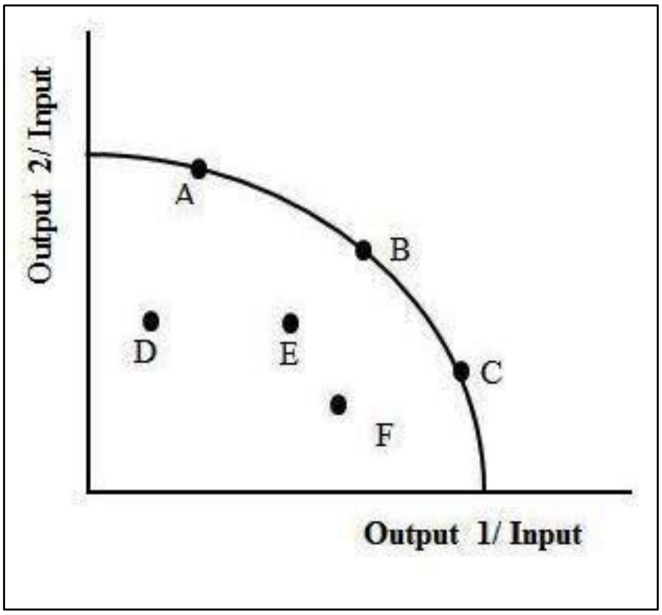
The main goal in DEA is to measure efficiency of each Decision Making Unit by calculating its resource usage to produce output. In every organizations or data set, there will be at least one best efficient DMU at the system. Therefore, DEA works under this assumption to evaluate the performance of each DMU by comparing with the best efficient DMU. Ozbek et al. (2009) claimed that efficiency scores are relative to the best efficient DMU or DMUs if more than one best efficient DMU exist at the data set. The main assumption is that if one DMU produces the output with a specific amount of inputs; then, the other DMUs can be able to produce same output with the same amount of inputs. However, if they produce less amount of output with using same amount of input or resources; then, they are counted as inefficient DMUs. Correspondingly, if they use more amount of input to produce the same output, they are similarly considered as inefficient DMUs. They need to find a way to become efficient by decreasing the input usage or increasing output with same level of input usage.

According to the characteristics of units or organizations, DEA willing to focus on input minimization or output maximization to measure efficient scores. This is the main perspective for optimization to determine whether maximize the produced value or minimize the resource usage. For instance, there are two data set with their envelops which are called k and m respectively. The first one, k, produces outputs with minimum input usage because of having constraints' rule and characteristics. Additionally, this envelop called as input oriented DEA program. The second one, m, willing to maximize its output with the given resources then it is called as output oriented DEA program.

Frontiers which can be also called as envelops are created by DEA to analysis the available data. According to Farrell (1957), these efficiency frontiers are also called as Frontier Analysis which is the basic forms of efficiency measurement. All DMUs can be compared with these frontiers to evaluate performance. Sample of efficiency frontiers can be seen in the Figure 3.1 and Figure 3.2 below. Figure 3.1 corresponds to an example of solving output maximization problem and Figure 3.2 is an example of input minimization in DEA.

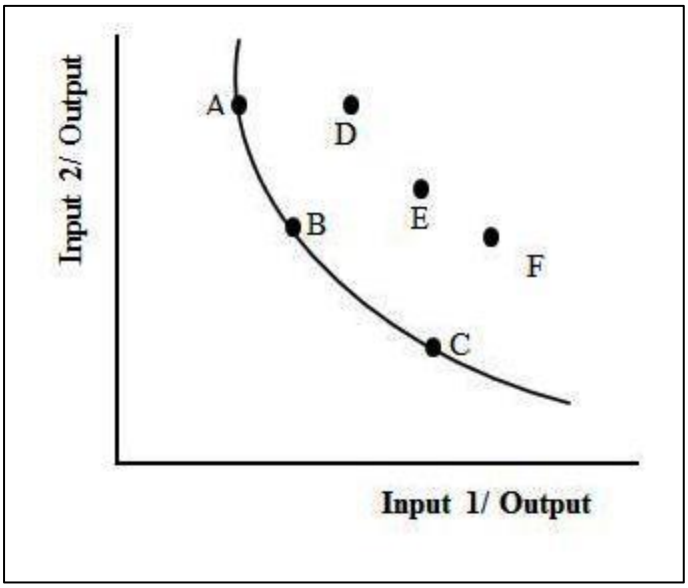
Figure 3.1 and Figure 3.2 are also example of DEA graphical representation. For example, in both figures, A, B and C are fully efficient DMUs since they are located at the efficient line. However, D, E and F are located out of these efficient lines then they are counted as inefficient DMUs.

Figure 3.1: Efficiency frontier; output maximization example



Source: Created by Ömer SAKA

Figure 3.2: Efficiency frontier; input minimization example



Source: Created by Ömer SAKA

3.1.2 General Mathematical Formulation of DEA

Graphical models cannot be useful when there are great number of inputs and outputs. For this reason, mathematical formulation is needed to solve the problems which have multiple inputs and outputs. First mathematical formulation was created by Charnes et al. (1978) and their study was the basic study of mathematical aspect of frontier analysis. The general mathematical model can be seen below (Ramanathan 2003:38):

$$\max E_m = \frac{\sum_{j=1}^{J} v_{jm} y_{jm}}{\sum_{i=1}^{I} u_{im} x_{im}} \qquad [3.1]$$

subject to

$$0 \leq \frac{\sum_{j=1}^{J} v_{jm} y_{jn}}{\sum_{i=1}^{I} u_{im} x_{in}} \leq 1; \quad n = 1, 2, \mathrm{K}, N \qquad [3.2]$$

$$v_{jm}, u_{im} \geq 0; \quad i = 1, 2, \mathrm{K}, I; \quad j = 1, 2, \mathrm{K}, J \qquad [3.3]$$

where
E_m is the efficiency of the mth DMU,
y_{jm} is jth output of the mth DMU,
v_{jm} is the weight of that output,
x_{im} is ith input of the mth DMU,
u_{im} is the weight of that input, and
y_{jn} and x_{in} are jth output and ith input, respectively, of the nth DMU, n = 1, 2, …, N.
Note that here n includes m.

This formula is the basic and general perspective of DEA. According to DEA model, variables may change depending on the problem; but, main goal of maximizing efficiency will be the same and not change. As it was mentioned at the beginning, DEA can be divided into two models; the first DEA model is CCR which assumes Constant Return to Scale (CRS) and second one is BCC which assumes Variable Return to Scale (VRS). Both of them will be explained below.

3.1.3 Constant Return to Scale Model

As discussed before, CCR DEA models are also named as CRS DEA models which is the basic form of DEA. The main idea is that the ratio of outputs to inputs should be optimized with solving weights for each output and input by using Linear Mathematical Formulation. Based on the purpose, this problem can focus on output maximization or input minimization. For both mathematical formulations are shown below with their explanations (Chiou and Chen, 2006):

For output maximization or Output Oriented CCR DEA model formulation;

$$\text{Max} \quad h \qquad [3.4]$$

$$\text{s.t.} \quad x_{kj} \geqslant \sum_{l=1}^{K} \lambda_l x_{lj}, \quad j = 1, 2, \ldots, J \qquad [3.5]$$

$$hy_{ki} \leqslant \sum_{l=1}^{K} \lambda_l y_{li}, \quad i = 1, 2, \ldots, I \qquad [3.6]$$

$$\lambda_l \geqslant 0, \quad l = 1, 2, \ldots, K \qquad [3.7]$$

Where

xkj is the *jth* inputs of the *kth* DMU,

yki is the *ith* outputs of the *kth* DMU,

kl is the weight multiplier of the lth DMU for both input and output,

K is the number of DMUs at the problem

I is the number of inputs,

J is the number of outputs

The main goal of this formula is to maximize the value of h with increasing *hyki* by increasing output *yki* of *kth* DMU. Therefore, This DMU will be relatively efficient with using same input *xkj*. When DMU is counted as efficient then h must be 1. This relativity comparison is related to the weights of each DMU's inputs and outputs.

For input minimization or Input Oriented CCR DEA model formulation;

$$\text{Min} \quad z \qquad [3.8]$$

$$\text{s.t.} \quad zx_{kj} \geqslant \sum_{l=1}^{K} \lambda_l x_{lj}, \quad j = 1, 2, \ldots, J \qquad [3.9]$$

$$y_{ki} \leqslant \sum_{l=1}^{K} \lambda_l y_{li}, \quad i = 1, 2, \ldots, I \qquad [3.10]$$

$$\lambda_l \geqslant 0, \quad l = 1, \ldots, K \qquad [3.11]$$

Where

xkj is the jth inputs of the *kth* DMU,

yki is the ith outputs of the *kth* DMU,

kl is the weight multiplier of the *lth* DMU for both input and output,

K is the number of DMUs at the problem

I is the number of inputs,

J is the number of outputs

The main goal of this formula is to minimize the value of *Z* with reducing *zxkj* by reducing the usage of input of *kth* DMU which is represent at this formula as *xkj*. Therefore, same output level *yki* will be reached then one of its DMU will be relatively efficient.

3.1.4 Variable Return to Scale Model

Due to the fact that the CCR or CRS models consider DMUs at the optimal conditions, it is not proper to evaluate efficiencies of DMUs when there are environmental factors such as competition, finance crises, etc. Therefore, BCC or VRS model is developed by Banker et al. (1984) to consider Variable Return to Scale situations.

The CRS model can easily be modified to VRS by adding one convexity constraint. For output and input oriented mathematical formulations can be seen below (Chiou and Chen, 2006);

For output maximization or Output Oriented VRS DEA model formulation;

$$\text{Max} \quad h \qquad [3.12]$$

$$\text{s.t.} \quad \sum_{l=1}^{K} \lambda_l = 1 \qquad [3.13]$$

$$x_{kj} \geqslant \sum_{l=1}^{K} \lambda_l x_{lj}, \quad j = 1, 2, \ldots, J \qquad [3.14]$$

$$h y_{ki} \leqslant \sum_{l=1}^{K} \lambda_l y_{li}, \quad i = 1, 2, \ldots, I \qquad [3.15]$$

$$\lambda_l \geqslant 0, \quad l = 1, 2, \ldots, K \qquad [3.16]$$

For input minimization or Input Oriented VRS DEA model formulation;

$$\text{Min} \quad z \qquad [3.17]$$

$$\text{s.t.} \quad \sum_{l=1}^{K} \lambda_l = 1 \qquad [3.18]$$

$$zx_{kj} \geqslant \sum_{l=1}^{K} \lambda_l x_{lj}, \quad j = 1, 2, \ldots, J \qquad [3.19]$$

$$y_{ki} \leqslant \sum_{l=1}^{K} \lambda_l y_{li}, \quad i = 1, 2, \ldots, I \qquad [3.20]$$

$$\lambda_l \geqslant 0, \quad l = 1, \ldots, K \qquad [3.21]$$

The meaning of convexity constraint ($\sum \lambda=1$) is that DMU is operating in its optimal scale. If this convexity index is $\sum \lambda>1$, operating scale of DMU will be reduced so this will called as Decreasing Return to Scale (DRS) and if it is $\sum \lambda<1$ then operation scale will be increased so it will called as Increasing Return to Scale (IRS).

According to selection of CCR or BCC models, two kinds of efficiencies are occurred: Technical Efficiency (TE) and Scale Efficiency (SE). Ramanathan (2003: 78) describes TE and SE as below;

> *"Technical efficiency describes the efficiency in converting inputs to outputs, while scale efficiency recognizes that economy of scale cannot be attained at all scales of production, and that there is one most productive scale size, where the scale efficiency is maximum at 100 per cent."*

While the CRS model is covering Technical Efficiency and Scale Efficiency by assuming the basic efficiency of a DMU, the VRS model evaluates pure Technical Efficiency considering scale of environment and variations.

3.2 MODEL SELECTION FOR STUDY

Data Envelopment Analysis is used with its model of BCC and also output oriented method is applied to measure the efficiency of routes with respect to the resources. Multi-stage perspective is considered depending on processing data and results.

The reason to select VRS instead of CRS is that there are lots of environmental factors that may affect the efficiency of routes. For instance, different number of competitors at the same route, market characteristics, passenger addictions to fly, natural disasters, politics of governments, etc. can affect the evaluation of route performance. Therefore, VRS model will be used at this study to evaluate the performance of air routes.

Inputs and outputs for DMUs which are air routes at this study will be defined and explain at the next part. However, it is better to mention about why to select output oriented approach to produce efficiency scores in the study: In Airline industry, some regulations and operational requirements such as weight load of aircraft, fuel consumption, number of staff and et. have to be fulfilled to maintain successful and safe operation. For instance, number of crew for each aircraft type are defined before operation and this number cannot be changed; otherwise, it is forbidden to fly according to international aviation rules. Moreover, according to distance, aircraft type and weather conditions, it is fixed and mainly cannot be reduced that how many tons of fuel will be fueled for specific routes and aircraft type. That is the reason why it is almost impossible to change inputs of routes to increase their performance. However, amounts or production of outputs can be changeable according to amendments of routes or administrative factor. Therefore, output oriented approach is selected to evaluate performance of routes and bring new perspective to increase their performance.

4. DATA ANALYSIS & RESULTS

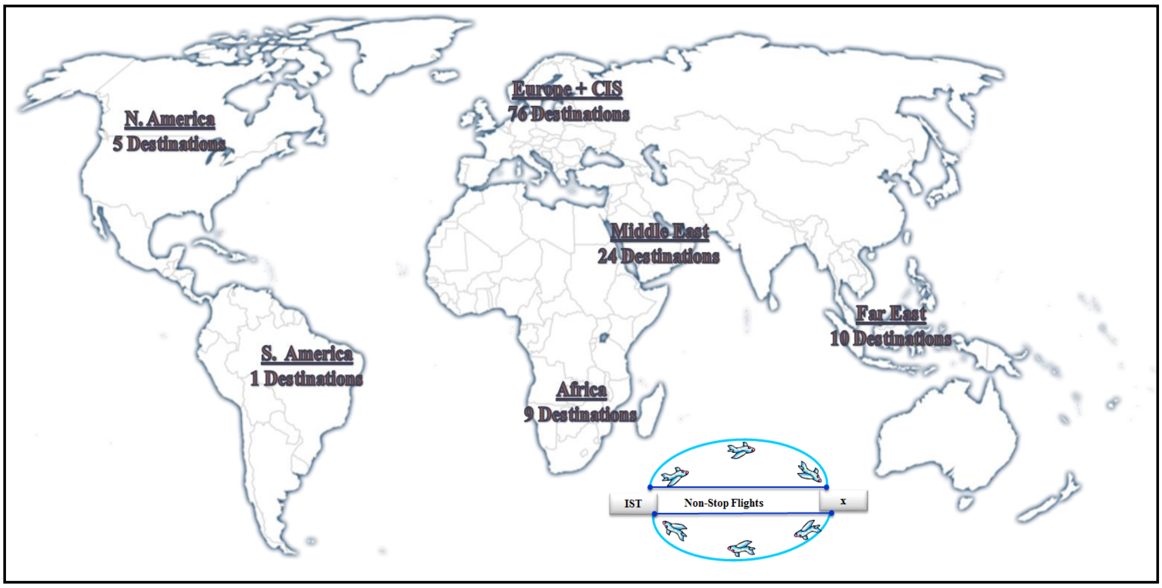
Data which are used in this study will be described in detail at this part. Also, input and output variables will be determined and explained one by one with the reasons why they are selected to use. After that, data will be analyzed and results will be interpreted with graphical illustrations.

4.1 DESCRIPTION OF DATA

Data of Turkish Airlines' 2011 international flight routes has been used in this study. Total of one hundred and twenty five international air routes were analyzed. Their regional distributions and locations are shown in Figure 4.1. Majority of these routes are located in the Europe and Middle East regions. Because of the confidentiality of the data, routes and countries will not be directly shown both at data description and result parts.

All routes include just non-stop flight data which shows any flight between two points by an airline with no change in flight number and do not include any intermediate stops, such as IST-TXL-IST (ISTANBUL-BERLIN-ISTANBUL), to have more realistic and accurate result, and also to contribute the productivity of routes after study. At Turkish Airline network, there are also direct flight and connect flight routes. A direct flight can be determined as any flight between two points by an airline with no change in flight numbers, which may include a stop at an intermediate point. The stop over may either be to get new passengers (or allow some to disembark) or a mere technical stop over (i.e., for refueling). When there is a change in flight number, the subsequent flight is referred to as a connecting flight. For instance, IST-JNB-CPT-JNB-IST is an example of direct market route and LHR-IST-TLV is an example of connect market route. The main difficulty for analyzing these routes especially for direct market routes is that it is not easy to determine inputs and outputs for these destinations. For instance, because of operating with same aircraft to these two destinations, cost of operation and some other variables cannot be attaining clearly. For this reason, only non-stop routes are considered to evaluate performance. Moreover, because of offering more flights to passengers and strategically locations to make operation, Turkish Airlines have also Antalya and Sabiha Gökçen Airports based operations besides Istanbul Atatürk Airport based at the network. These each based operations are targeting different markets and structure, so only Istanbul based routes are considered at this study to evaluate performance.

Figure 4.1: Regional distribution of destinations at the study

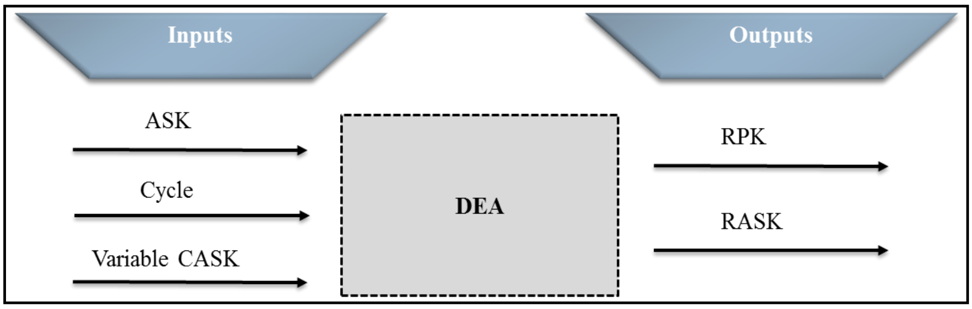


Source: Created by Ömer SAKA

4.2 VARIABLE SELECTION

In the airline sector various factors may affect the performance of routes. Especially, for the wide network carriers like Turkish Airlines, these factors become more crucial to find out accurate results by evaluating each routes. Thus, most important and correlated variables are selected for input and output data which can be seen at the Figure 4.2. The description of input and output variables and their rational to select for this study will be explained at the following paragraphs.

Figure 4.2: Input and output variables at the study



Source: Created by Ömer SAKA

Three variables are selected as inputs which are ASK (Available Seat Kilometers), Variable CASK (Variable Cost per Available Seat Kilometers) and Cycle.

ASK is calculated by multiplying the number of seats on an aircraft by the distance travelled in kilometers. It is used to measure an airline's capacity to transport passengers. The reason to select ASK for input variable instead of physical seat capacity for each flight is that it normalizes the capacity for each route and gives better chance to compare with others by multiplying the distance of each route. In the Turkish Airlines network, different types of aircrafts are assigned to different distance of routes in various countries and cities. For instance; for New York route, Boeing 777 aircraft type which has total 337 seat capacity is assigned and from İstanbul to New York is approximately 8060 kilometers. However, for Berlin rote, Airbus 321-200 type of aircraft which has total 210 seat capacity is assigned and from İstanbul to Belin is approximately 1742 kilometers. Therefore, it is hard to define capacity by only considering seat capacity of aircrafts. This problem can be solved by considering capacity with distance calculation.

Some previous related studies also selected ASK as the input variable for performance measurement. For instance, Charnes et al. (1996) selected available seat-kilometers as input to evaluate the Latin American airlines' domestic and international operations by using DEA. Merkert and Hensher (2011) selected available seat-kilometers as input to evaluate the impact of strategic management and fleet planning on airline efficiency. Lu et al. (2012) also chose ASK as intermediate-input variable to measure the effects of corporate governance on airline performance with the production and marketing efficiency perspectives.

CASK is calculated by dividing total operating cost by ASK. It is also one of the common units to measure unit cost of airline or particular route of an airline. Variable CASK represents the cost of variables such as fuel cost, maintenance, navigation fee, handling, catering, landing, and etc. which gives more convincing way to measure efficiency of specific routes. The reason to select variable CASK for input variable is that it is one of the main parameters to measure efficiency at the airline sector. It is considered as unit cost of specific route or cost per capacity. Moreover, selecting variable CASK instead of total CASK (which also includes fix costs) gives more specific perspective to measure each route's operational costs, because fix costs are common expenses which also include different and unrelated part of the company for the routes such as telecommunication fees, aircraft insurance, crew salary, advertisement expenditures, and etc.

Some previous studies did not chose variable CASK directly but they used main parts or units of variable CASK as the input variable for performance measurement. For example, Charnes et al. (1996) selected fuel cost as input variable which is presenting main part of the variable CASK units. Tofallist (1997) also selected operating cost which is also can be counted as main portion of variable CASK, as input variable to evaluate airline performance.

Cycle can be described as single take-off and landing of an aircraft, and is referred to one flight cycle. Because of different frequencies at the routes, considering the cycle as input variable leads the system to analyze them properly. For instance, IST-LHR-IST (ISTANBUL-LONDON-ISTANBUL) has 28 frequencies in a week but IST-JFK-IST (ISTANBUL-NEW YORK-ISTANBUL) has 14 frequencies each week. Therefore, measuring route efficiency by normalizing all routes is only possible to put cycle as input variables.

Two variables are selected as outputs which are RPK (Revenue Passenger Kilometers) and RASK (Revenue per Available Seat Kilometer).

RPK is a measure of the volume of passengers carried by an airline. It shows the number of miles traveled by paying passengers. Revenue passenger kilometers are calculated by multiplying the number of paying passengers with the distance traveled. It is described as a measure of sales volume of passenger traffic. All input and output variables should be correlated with each other to have more accurate results. For this reason, RPK considered as output variable versus ASK as the input variable. It also very important parameter at the airline industry to measure company efficiency at the sales volume. Capacities of each route defined with ASK and with RPK find out that how many of this supplied capacity has been sold.

RPK was selected as the output variable in the performance measurement for the airline sector by some previous related studies. For example, Banker and Johnston (1994) adopted the revenue passenger-miles as output and applied DEA to evaluate the impacts of operating strategies on efficiency in the US airline industry. Charnes et al. (1996) also chose passenger-kilometers as output to evaluate the Latin American airlines' domestic and international operations by using DEA. Scheraga (2004) also selected revenue passenger- kilometers as output to investigate operational efficiency and financial mobility for 38 airlines.

RASK is calculated by dividing operating revenue to available seat kilometers. It has been adopted as a standard unit of measurement by most airlines. Similar relationship between RPK and ASK can be seen between RASK and CASK. In addition, RASK is correlated with variable CASK. It is very obvious that by selecting RASK as output gives an idea of what is unit revenue of specific route versus unit cost of it.

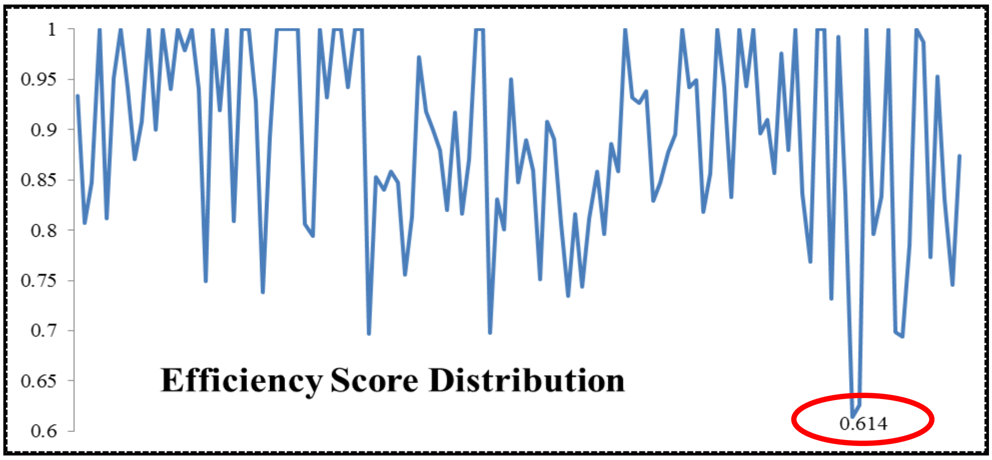
4.3 DATA ANALYSIS AND RESULTS

4.3.1 Efficiency Scores and Graphical Illustration

Computer program -DEAP version 2.1 which was developed by Tim Coelli (1996) - is used to calculate efficiencies for each route. As it was aforementioned, BCC or Variable Return to Scale (VRS) output oriented method is applied to measure the efficiency of routes. All these factors were described in the software and run at different combinations.

Firstly, whole data of 125 DMUs is considered without any separation or division to regions. After running the software, the efficiencies of routes are calculated, but the values are varied and hard to interpret one by one. Therefore, distribution of results which are shown in Figure 4.3 is a better way to see results. It is also seen in Figure 4.3 that minimum efficiency sore is 0.614 and scores are changing mostly between 0.80 and 0.90.

Figure 4.3: Efficiency score distribution



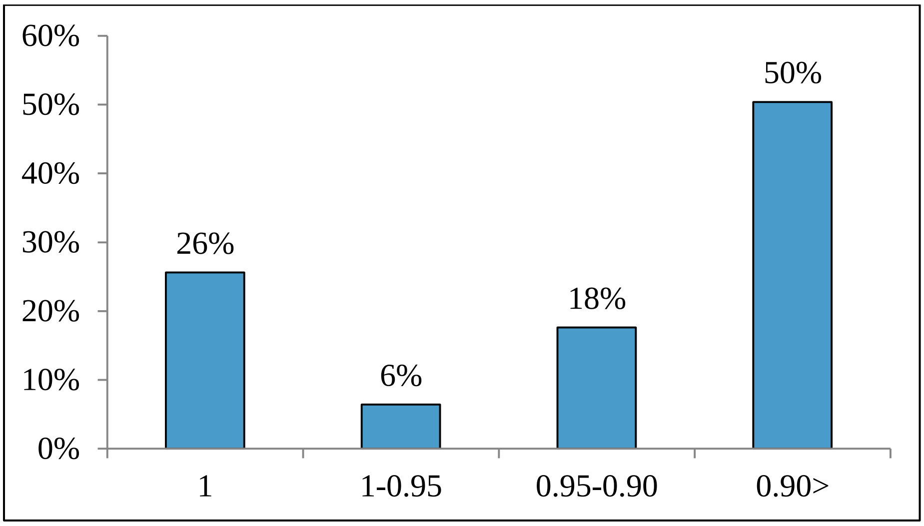
Source: Created by Ömer SAKA

4.3.2 Comparison of Efficiency Scores

Efficiency scores are categorized into four groups based on their scores to understand and analyze them better. First group includes scores of equal to 1 which are the most efficient routes at the data; second group includes scores between 1 and 0.95; third group includes scores between 0.95, and 0.90 fourth group includes scores les then 0.90.

According to results which are also shown in Figure 4.4; 26 percent of routes are efficient, 6 percent of them are in the second group, 18 percent of them are in the third group and 50 percent of them are in the fourth group.

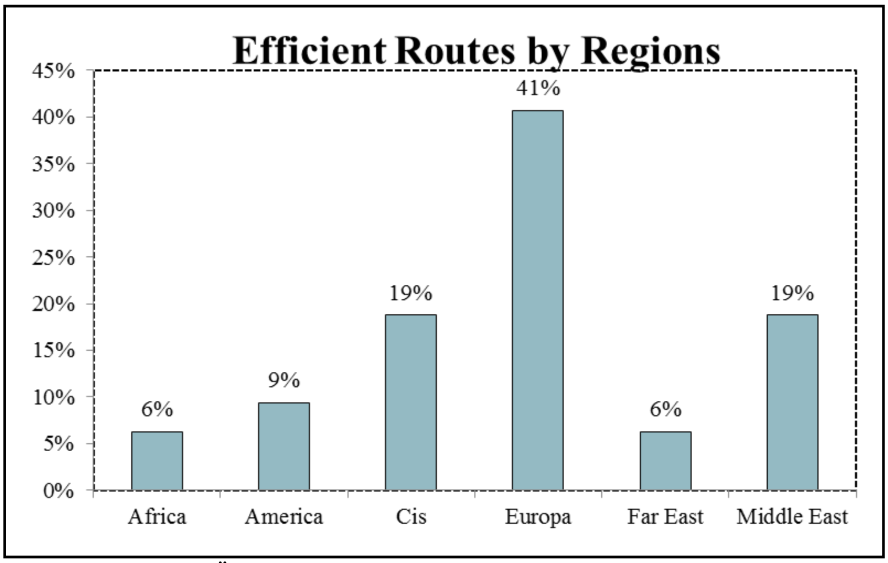
Figure 4.4: Efficiency of routes



Source: Created by Ömer SAKA

To understand the reason why efficient routes are efficient while the rest of routes are inefficient, efficient routes are divided by regions to give better perspective to interpretation. 26 percent of efficient routes are spitted into regions in Figure 4.5. The most of efficient routes are found in Europe, Middle East and CIS regions which Turkish Airlines' density of main operations (around 80 percent), are located in these regions and which are the oldest flying destinations at the network.

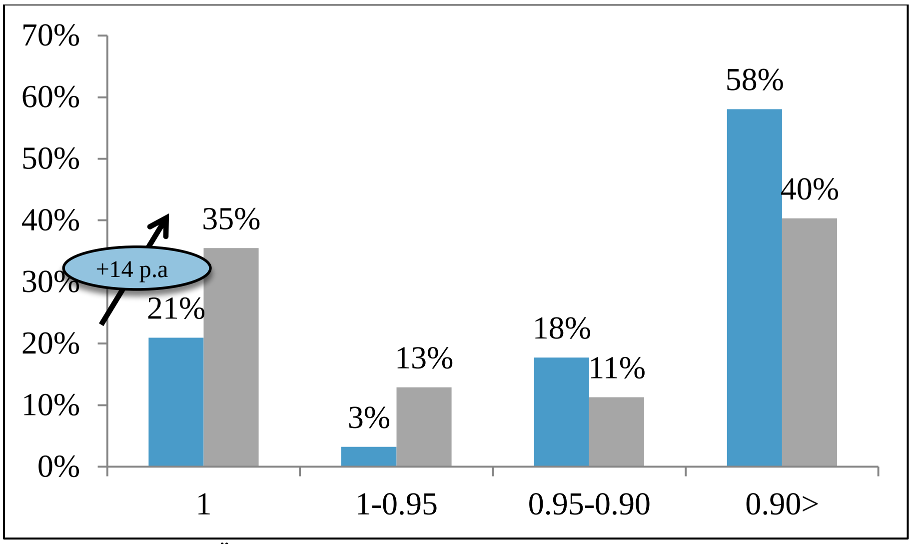
Figure 4.5: Breakdown of efficient routes into the regions



Source: Created by Ömer SAKA

Since all markets and regions have different characteristics such as competition, passenger addictions to travel, trade volumes, economic factors, political factors, Turkish Airlines' number of frequency at the routes, aircraft types which fly at these routes, products to offer, connectivity quality factors and etc. may affect the routes' performances. Therefore, dividing these routes into the regions and analyzing them accordingly, give better results. For this reason, DEAP software is run again with same DEA model and criteria is split region by region. Routes located in Europe are given in Figure 4.6 as a sample of these different size and characteristic analyses. As it is seen that number of efficient routes increased by 14 percent with respect to the first results. Also, it can be said that less than 0.90 efficient score routes and routes between 0.95 and 0.90 efficient scores shift to the efficient or second group of efficient routes. Therefore, we can conclude that evaluating routes efficiency according to their market characteristics gives more accurate results than the whole market evaluation.

Figure 4.6: Comparison of Europe routes by data size

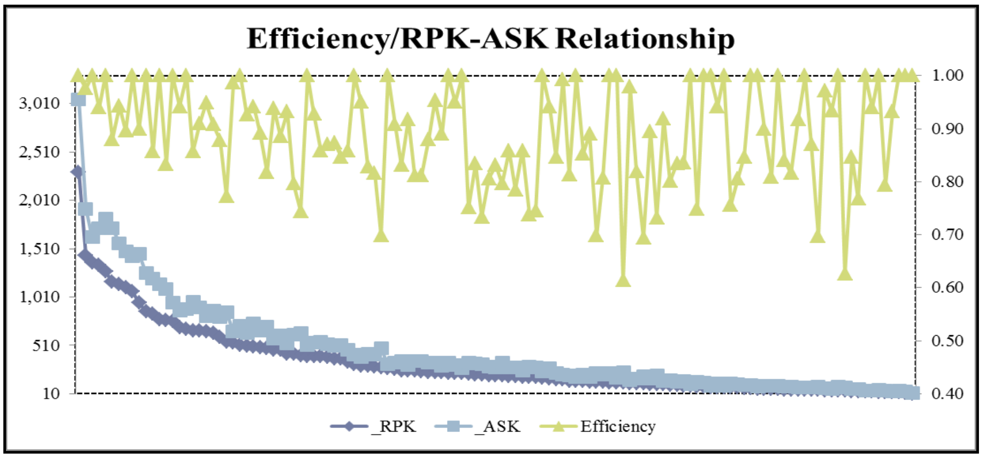


Source: Created by Ömer SAKA

4.3.3 Relationship between Efficiency Score and Load Factor

One of the main factors that affects efficiency of routes is load factor (LF) which is calculated by dividing RPK by ASK. It shows how much of the capacity has been sold to gain revenue. Moreover, it is also clearly seen in Figure 4.7 that there is positive relationship between efficiency and LF. The score of efficiency gets close to 1.0 while the LF increases. For this reason, it can be concluded that marketing and administrative activities affect the efficiency of routes.

Figure 4.7: Efficiency and RPK-ASK relationship



Source: Created by Ömer SAKA

4.3.4 Grouping Routes

Routes are categorized into the three groups for better analyzing and interpretations. According to characteristics and market similarities of routes which are locating into five different regions, routes are grouped into three groups based on market conditions and flying distance. As shown in Table 4.1, these one hundred and twenty five routes are grouped as Group 1, Group 2 and Group 3.

Table 4.1: Average efficiencies of regions and group of routes

First Groups of Routes			Second Groups of Routes		
Region	**Number of Units**	**Mean**	**Groups**	**Number of Units**	**Mean**
Africa	9	0.94	Group 1	76	0.89
Middle East	24	0.86			
Far East	10	0.96	Group 2	16	0.96
America	6	0.97			
Cis	14	0.92	Group 3	33	0.88
Europa	62	0.88			

Source: Created by Ömer SAKA

4.3.5 Descriptive Analysis

Table 4.2 presents the descriptive statistics concerning input and output measures for Group 1, Group 2 and Group 3 routes. According to results, there are statistically significant differences among the different groups of routes in both output and input variables. ASK and RPK has the highest figures in Group 2 as a result of having long range of destinations in this group. Additionally, Variable CASK and RASK have the lowest figures in this group because of flying distance. As a result of these facts, Group 2 has the highest efficiency scores and this clearly indicates how these variables affect the efficiency of routes. While Group 1 and Group 3 has high figures in RASK, their efficiency scores are lower than Group 2 because of having lots of routes which are located in different countries and cities. Also, standard deviation figures of these groups are obviously proof this claim. These findings are not particularly surprising, and quite fit to the expectations.

Table 4.2: Variable details along with efficiency scores based on the groups

		Groups							
		Group 1		Group 2		Group 3		Total	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Inputs	ASK (x1000000)	319	297	1,446	562	298	210	457	498
	Variable CASK	6.53	1.92	4.67	0.31	5.81	1.10	6.10	1.71
	Cycle	1,086	744	607	217	890	604	973	679
Outputs	RPK (x1000000)	234	233	1,041	436	206	161	330	371
	RASK	9.83	3.05	6.40	0.99	9.64	3.33	9.34	3.14
Number of Routes		76		16		33		125	
Efficiency Scores		0.89		0.96		0.88		0.89	

Source: Created by Ömer SAKA; Note: S.D. =Standard deviation

4.3.6 Comparison of Regional Differences among Categories of Routes

DEA study in first section has focused on the overall efficiencies where there is no assumption of administrative and structural differences among the different regions. After that, in the second step of analysis, routes were considered as separately and these results were more accurate than the first one. However, comparison of routes into the same region is not enough to evaluate them as whole network. Therefore, routes are needed to compare with also other routes which are locating different regions. The market conditions and administrative differences may vary in each group of routes, and competition among the groups may not be identified clearly due to market characteristics. Brockett and Golany (1996) suggest a methodology to determine categorically inherent efficiency differences in DEA, where Sueyoshi and Aoki (2001) extend their study later to handle many categories instead of only two.

In order to eliminate regional differences and identify structural differences in this study, each group of routes are evaluated separately in line with the procedure suggested by Brockett and Golany (1996) and Sueyoshi and Aoki (2001). In each group, inefficient routes are projected into their efficiency frontier, and a new pooled DEA (with output oriented BCC approach) is run including all groups at their adjusted efficiency levels. Efficiency scores of all groups as well as their comparisons through Kruskal-Wallis Rank test are shown in Table 4.3.

Table 4.3: Kruskal-Wallis rank test results for structural differences

Output-oriented BCC model for:	Efficiency Scores		KW	p-value
	Mean	**S.D.**		
Group 1	0.99	0.012	19.596	0.01
Group 2	0.98	0.030		
Group 3	0.96	0.049		

Source: Created by Ömer SAKA; Note: S.D. =Standard deviation; KW= Kruskal-Wallis score

Eliminating the effect of administrative differences in all groups of routes lets us to focus more on the structural differences among them. In fact, Kruskal-Wallis Rank test result in Table 4.3 shows that there are some differences among the groups based on their characteristics of routes ($p < 0.01$). Indeed, Group 1 routes are the most efficient ones followed by the Group 2. It is remarkable that Group 3 is the least efficient ones. The pairwise comparisons represented in Table 4.4 indicate that the efficiency difference between Group 1 and Group 3 is statistically significant while there are not much significant difference both between Group 1 and Group 2; and Group 3 and Group 2 ($p < 0.01$).

Table 4.4: Rank sum test results for pairwise comparisons of groups

Comparison of Groups			
Group Pairs	**KW**	**S.D.**	**Sig**
Group 3-Group 1	31.072	7.186	0
Group 2- Group 1	18.151	9.481	0.219
Group 3-Group 2	12.920	10.5	0.056

Source: Created by Ömer SAKA; Note: S.D. =Standard deviation; KW= Kruskal-Wallis test score

The structural differences may be explained from the several viewpoints. Firstly, Group 3 and Group 1 routes have some significant administrative inefficiency and competition environment compared to their peer routes in their categories. Dealing with these administrative deficiencies makes Group 1 and Group 3 more efficient. Secondly, market characteristics of Group 1 and Group 3 help them achieve better efficiency scores. On the other side, Group 2 aligns the deficiencies raised by the some technical and governmental restrictions such as slot problem and flying permissions.

For further analysis of the results, it is necessary to study the technical inefficiencies in terms of the input excesses and the output deficits, which are summarized in Table 4.5 and 4.6. The average slacks for variables considered in DEA model derived from each group individually are presented in Table 4.5. In Group 1 and Group 3, ASK and RPK should be focused while Group 2 should only improve ASK to reach more efficiency level. This result is not surprised and as already explained Group 2 has some governmental problems to increase frequency and having more slot permissions. Therefore, if these problems are solved and ASK will increased, then Group 2 routes will become more efficient.

Table 4.5: The source of inefficiencies within the groups

		Average Improvement Potential of Groups		
		Group 1	**Group 2**	**Group 3**
Input Excesses	ASK	4,664,463	8,020,494	1,988,414
	Variable Cask	0.06	0.01	0.29
	Cycle	412	23	422
Output Deficits	RPK	386,691	-	114,201
	RASK	0.78	0.16	0.28

Source: Created by Ömer SAKA

Table 4.6 shows the average slacks for variables derived from the DEA model to measure the structural differences among the groups. These results depict almost the same picture which was shown in Table 4.6. Group 1 and Group 3 have potential improvements in RPK while Group 2 only has potential improvement in ASK.

Table 4.6: The source of inefficiencies among the groups

		Average Improvement Potential of Groups		
		Group 1	**Group 2**	**Group 3**
Input Excesses	ASK	-	14,158,413	412,810
	Variable Cask	0.12	0	0.08
	Cycle	441	0	340
Output Deficits	RPK	323,448	-	353,684
	RASK	0.66	0.03	0.33

Source: Created by Ömer SAKA

4.3.7 Comparison of Returns to Scale

In the analysis of efficiency, returns to scale is another facet of evaluation. Banker et al. (1984) classify the scale efficiency of DMUs into three categories: (i) increasing returns to scale (IRS); (ii) constant returns to scale (CRS); and (iii) decreasing returns to scale (DRS). IRS means that an increase in input will result in a greater than proportionate increase in output, whereas DRS is the case where the result is less than the proportionate increase in output. CRS is exhibited where the result is the proportionate increase in output. Then, the groups based on their types of routes are classified into these three categories by their returns to scale. The numbers and distributions of the groups within these three categories of the returns to scale are shown in Table 4.7a and Table 4.7b.

Table 4.7a shows the returns to scale of groups before categorization. According to results, 54.40 per cent of routes are listed under the IRS and 9.60 per cent of them are listed under CRS while only 36 per cent of routes are in the DRS. Including 9.60 per cent of the routes categorized under CRS, the number of routes listed as IRS or CRS reaches a total of 64 per cent of them. Therefore, majority of the routes have a potential to increase their outputs either proportionally or over proportionally with their increment on inputs. It should be noted that Group 1 fallen in DRS category are the highest with 42.11 per cent, and the lowest in IRS category with 50 per cent.

Table 4.7a: Categories of returns to scale, before categorization of routes

	DRS		CRS		IRS		Total
	Number	Percent	Number	Percent	Number	Percent	
Group 1	32	42.11	6	7.89	38	50.00	76
Group 2	2	12.50	4	25.00	10	62.50	16
Group 3	11	33.33	2	6.06	20	60.61	33
Total	45	36.00	12	9.60	68	54.40	125

Source: Created by Ömer SAKA

Table 4.7b shows the returns to scale of groups after categorization of routes. It is clearly indicate that in Group 1, almost 10 per cent of routes which were listed under DRS in Table 4.7a shifted to CRS and almost 14 per cent of routes listed under IRS shift to CRS. Therefore, structural differences within Group 1 are significant and categorization of routes affects this group more than the others. While, total of IRS and CRS routes reach 69.60 per cent, there is no significant difference between the after categorization and before categorization of routes in terms of their returns to scale characteristics.

Table 4.7b: Categories of returns to scale, after categorization of routes

	DRS		CRS		IRS		Total
	Number	Percent	Number	Percent	Number	Percent	
Group 1	25	32.89	23	30.26	28	36.84	76
Group 2	2	12.50	4	25.00	10	62.50	16
Group 3	11	33.33	2	6.06	20	60.61	33
Total	38	30.40	29	23.20	58	46.40	125

Source: Created by Ömer SAKA

5. CONCLUSION

This study aims to assess the performance of international flight routes of Turkish Airlines in 2011 by executing their resource allocation and productivity perspective. Data Envelopment Analyses (DEA) is used with its model of BCC or Variable Return to Scale (VRS) output oriented method to measure the efficiency of routes with respect to the resources. A total of one hundred and twenty five non-stop flight routes which are located in different regions and markets are examined. All individual routes are treated as DMUs to evaluate the performance of specific routes. Three variables are selected as input which are ASK (Available Seat Kilometers), Variable CASK (Variable Cost per Available Seat Kilometers) and Cycle. On the other hand, two variables are selected as output which are RPK (Revenue Passenger Kilometers) and RASK (Revenue per Available Seat Kilometer).

The results of one hundred and twenty five routes demonstrate that efficiency scores are various and results scores are changing between 0.614 and 1.0 scale. For better understanding and interpreting the results, these scores are categorized into four groups based on their efficiency scores. 26 percentages of routes are into the first group and they are the most efficient routes at the network; second group includes scores between 1 and 0.95 and they covers 6 percentages of network; third group includes scores between 0.95, and 0.90 and they covers 18 percentages of network; fourth group includes scores les then 0.90 and they comprises 50 percentages and majority of routes at the network.

The efficient routes are divided into the regions for better evaluation. Furthermore, Europe regions are the most efficient routes with 41 percentages; Middle East and Cis regions are the second efficient regions with 19 percentages; 9 percentages locating in Amerika and Africa and Far East region compromise 6 percentages of these efficient routes. It can be claimed that route performance depends on characteristic of markets and also flying years at the specific routes.

One hundred and twenty five DMUs' evaluation is hard to figure out in terms of inefficiency reasons and to better interpret them. For this reason, routes are divided into the three groups according to their characteristics and market conditions and they are analyzed as considered separately. The results demonstrate that efficiency scores are increased and give more realistic results to evaluate them.

As suggested by Brockett and Golany (1996), the structural efficiency differences among the different groups were also measured by eliminating the administrative and regional differences in each group. A significant structural difference was found among the different groups. Group 1 was measured as the most efficient ones followed by the Group 2. It was also found that Group 3 was the least efficient ones. The main structural differences found statistically significant between the Group 3 and Group 1 by using Kruskal-Wallis rank test. For Group 1 and Group 2, ASK and RPK has potential to be improved while Group 2 only needs to improve ASK to get better efficiency scores. In terms of returns to scales, 64 per cent of the routes were classified either CRS or IRS. So, this might indicate that routes in related group have still potential to increase their efficiency.

In conclusion, because of every route covers different customers, competitors and market characteristics, its operating plans and administrative actions had better to be proposed from a route-base view. For this reason, this study is the first research to evaluate international routes with this perspective. Based on the analysis and efficiency results, it can be concluded that route markets and characteristics are direct affect to performance of routes. For this reason, evaluating routes efficiency according to their market characteristics gives more accurate results than the whole market evaluation. Moreover, load factor has very important role of improving efficiency of routes. Therefore, marketing and sales activities should be increased for each route to increase load factor. Finally, some administrative and governmental restrictions have direct effect on efficiency of routes. Therefore, it is suggested that routes should be examined with this constraints.

Only route-based evaluation may not be efficient way to evaluate performance of routes in complex airlines network. For instance, one route can be inefficient but it also feeds other route or routes with transfer passengers. For this reason, for better evaluation network contribution factor should be considered to have better and accurate results. Furthermore, because of having different number of competitors at the specific markets and routes, competition factor should be considered while analyzing them and comparing them with each other.

For further research I recommend that network contribution and competition should be considered to have better results. Also, routes should be evaluated at their relative markets and be considered with similar environmental factors.

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